USER PREFERENCES FOR BICYCLE INFRASTRUCTURE AND THE IMPACT OF INFRASTRUCTURE ON BICYCLE TRIPS

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USER PREFERENCES OF BICYCLE INFRASTRUCTURE AND THE IMPACT OF INFRASTRUCTURE ON BICYCLE TRIPS

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LIST OF SYMBOLS AND ABBREVIATIONS

AASHTO	American Association of State Highway Transportation Officials
ACS	American Community Survey
GDOT	Georgia Department of Transportation
ORNL	Oak Ridge National Laboratory
NCHRP	National Cooperative Highway Research Program
NHTS	National Household Transportation Survey

SUMMARY

Bicycling for transportation is experiencing a resurgence in much of the U.S. Consequently, the question of facility design has become a hot research topic. However, most such research is conducted in areas with strong bicycling cultures, which misses a critical link of how facility design can help shape bicycling culture. This dissertation contains analyses on data from a dual-wave survey deployed between 2016 and 2018 in communities in the Southern United States. To varying degrees, these are communities where cycling is not (yet) popular and/or widely adopted, a setting that is much more representative of the nation at large.

The first analysis is on a subset of the data from the first-wave survey (N=1,178), in which quantitative analyses including linear regression models are used to estimate perceived comfort, perceived safety, and willingness to try bicycling facilities. Facilities that limited interaction with automobile through, turning, and parking traffic were found to be perceived as more desirable among cyclists. The second analysis contains the full first-wave sample (N=2,157) including respondents in neighborhoods in Atlanta, GA. Latent class models were estimated with attitudinal factors such as bicycle enjoyment and risk tolerance as class membership covariates, with results indicating the presence of a latent class of pro-bicycling but risk-cautious respondents whose perceptions differ from those of their pro-bicycling, risk-embracing counterparts by the relatively greater impact of protected bicycle facilities. The final analysis of the dissertation is conducted on before-and-after survey responses (N=807) from all ten sites, with five sites serving as treatment communities (where bicycling facility treatments were implemented over the course of the study) and five serving as control communities (where no such bicycling facility treatments were implemented). Linear regression and ordered logit models are estimated using respondents' perceptions of changes in bikability in their neighborhood. Those in the treatment group were more likely to rate observed changes as improvements, though the effect of on-street facilities diminished for those farther from the treatment. These results provide key takeaways regarding expectations for the impacts of bicycling facilities in places where bicycling for transportation is viewed as rare, which can provide an additional tool for planners and engineers in making the case for the implementation of bicycle facilities.

CHAPTER 1. INTRODUCTION

1.1 Background

Despite the wide array of available modes of transportation, the U.S. has traditionally been automobile-focused, which has resulted in marginalization of healthy and active modes of transportation like cycling and walking. This marginalization of active modes has a substantial impact on air pollution, results in dependence on international sources of fuel, and contributes to an alarming increase in obesity, heart disease and asthma among both adults and children (Sallis 2004). However, only about 1% of all trips made in the U.S. are by bike (AASHTO 2012). Given that about 36% of US adults are obese (Ogden et al. 2012) and that the transportation sector accounts for 28% of US greenhouse gases (ORNL 2011), planning agencies have come to recognize bicycling as an active mode of transportation that may have huge potential when incorporated as part of sustainable transportation planning. Despite the monetary investments required for interventions aimed at increasing cycling, the monetized social benefits in the form of fuel savings and health-care savings resulting from increased cycling activity can potentially outweigh the initial financial investments (Gotschi 2011).

The most commonly stated reason for not using cycling as a mode of travel is the perception of inadequate safety associated with it (AASHTO 2012; Klobucar and Fricker 2007; Akar and Clifton 2010). Major factors contributing to this perception are high speed limits, high traffic volumes, and the absence of dedicated facilities for cyclists that provide a physical separation from vehicular traffic (Dill and Carr 2003, Buehler and Pucher 2012). Most importantly, facilities are often on isolated segments of streets and do not form a continuous network, thus failing to provide the perception of safe bicycling routes to destinations and undermining their own utility (Schoner and Levinson 2014).

While reasons to pursue cycling as a sustainable alternative and complement to vehicular transportation are well documented, accurate and robust data to support decisions on where and how to best develop new cycling infrastructure remain elusive. Regional surveys tend to have a very small sample of cyclists, since bicyclists constitute a marginal proportion of total traffic. There is also little data describing potential cyclists—who they are, the barriers that inhibit their cycling, and how infrastructure investments may help to overcome these barriers. As a result, there is little understanding of the latent demand from either current or potential cyclists who do not presently feel safe due to a lack of appropriate infrastructure. Cities with the intention of increasing cycling face two significant challenges: quantifying the effectiveness of interventions and justifying allocation of resources for cycling (Handy et al. 2014).

1.2 Study Objectives and Approach

The primary objective of this research is to understand the preferences for bicycle infrastructure and how these preferences can change. This thesis covers how preferences can change based on how both current and *potential* cyclists respond to different types of cycling infrastructure.

To meet this objective, a comprehensive data collection and analysis process has been designed to improve the understanding of how people make choices about daily travel (in particular referring to the adoption, or lack thereof, of active modes of transportation), focusing on a region of the U.S. where a cycling culture is just emerging.

The research is intended to answer several key questions, including:

- What are the relative preferences of current and potential bicycle users for different types of bicycle facilities?
- How do such preferences vary by demographic and attitudinal characteristics?
- What role do bicycle facilities for play in perceptions of improved bikeability and changes in travel behavior?

This study offers a unique opportunity to explore the factors affecting the travel behavior of different types of current and potential cyclists, and the way in which new infrastructure projects affect the travel choices of residents in regard to the adoption of cycling.

The overall approach to understanding the relative preference for and relative effectiveness of various kinds of bicycle facilities among current and potential cyclists is cross-sectional and quasi-experimental. The primary data source comes from responses to a survey of current cyclists and non-cyclists, which measured perceptions of different infrastructure types, together with numerous other variables. This approach provides a framework for estimating relative preferences for different variables for different segments of current and potential users. Key dependent variables include measures of perceived safety, comfort, and willingness to try biking on a bicycle facility, as well as perceived improvements to bicycle facilities and safety. Analyses control for individual characteristics and infrastructure components, namely the type of bicycle facility, on-street parking, and the number of automobile lanes.

1.3 Outline of the Dissertation

The following chapter includes a detailed review of the literature regarding user preferences of bicycle infrastructure. There is a plethora of findings regarding the preferences and behaviors of current cyclists and those in cities with a well-established culture of cycling. However, there is a significant gap regarding the preferences of those who do not currently cycle as well as those who reside in a community where cycling is not prevalent.

Chapter 3 of the dissertation describes the survey design and deployment areas. The survey was designed to measure stated preferences for and perceptions of bicycling facilities, and was distributed to over 40,000 potential respondents among both treatment and control sites. It was confirmed that (as planned) each treatment site had somewhat similar observed characteristics to its respective control site, while the differences that were observed are controlled for in later models. Statistics segmented by rider type are also reported, which reveal distinct differences in observed characteristics among different rider types. These statistics reveal several patterns that are further addressed in the following chapter.

Chapters 4, 5, and 6 contain the data analyses of the dissertation. The focus of Chapter 4 is on analyses conducted to investigate perceptions of and preferences for bicycling facilities based on bicycling frequency on first-wave responses from the initial 6 sites (N=1,178). The contents of this chapter are also found in Clark et al. (2019), which was recently published in *Transportation Research Record*. Chapter 5 contains complete analyses of the entire set of first-wave responses (N=2,157). It builds upon the previous chapter by including a larger and more diverse sample and using attitude-based latent classes to address taste heterogeneity in modeling the preferences for bicycling facilities, and has been submitted for publication in a high-quality journal. Chapter 6 details the analysis of second-wave survey responses (N=855) with a focus on investigating the impact of bicycling facility treatments on perceptions of bikability. A paper based on this analysis is undergoing preparation for submission to a currently undetermined journal.

Finally, the conclusion of the dissertation is found in Chapter 7. The major contributions of the dissertation are reiterated in this chapter. Explanations of limitations and suggestions for future work are also included.

CHAPTER 2. LITERATURE REVIEW

A search of the literature was conducted using primarily the TRID database. Preference was given to papers written in English with American data, though some English papers of particular relevance with international data were also reviewed. This chapter contains a review of the literature applicable to bicycling infrastructure and the perceptions, preferences, and use of such infrastructure by potential and current cyclists.

2.1 Research Design

Much of the current literature regarding bicycle demand is devoted to assessing the effectiveness of additional facilities on increasing cycling rates; however, there are substantial gaps in the literature to date. Many of these studies did not adequately explain their measures or methodology, did not use a treatment and control methodology, were not peer-reviewed, relied on samples from existing cyclists only, or biased the sample by stressing the focus on cycling at the outset (Pucher et al. 2010). This section includes an overview of research designs that have been undertaken in the topic of forecasting the effects of cycling infrastructure, along with their limitations.

Early studies in a new area of travel behavior research typically employ cross-sectional methods with a sample of the population at a single point in time to establish associations between observed behaviors and possible factors influencing such behavior (Krizek et al. 2009b). The first major study of this nature, Nelson and Allen (1997), evaluated data from 18 major U.S. cities, and built a basic linear regression model indicating a loose correlation between miles of bicycle infrastructure and cycling rates. Other aggregate-level studies followed suit in efforts to explain inconsistencies observed throughout different cities by increasing the number of cities and variables, with Dill and Carr (2003) using a similar regression model on data from 43 large U.S. cities, and Buehler and Pucher (2012) using data from 90 of the 100 most populous U.S. cities. Both of these studies confirm a correlation between infrastructure availability and bicycle commute mode share. On the more granular census tract level, Teschke et al (2017) performed a study in Vancouver and Montreal, identifying that living in tracts near bikeways, especially cycletracks, was associated with a greater probability to bike. However, cross-sectional aggregate studies reveal only correlation—not causality. Consequently, these studies fall short of adequately answering the question of whether cycling preceded infrastructure or vice versa.

Other studies have taken a disaggregate approach to identifying the effects of infrastructure. User's propensity to cycle is positively influenced by the presence of dedicated infrastructure (Moudon et al. 2005; Krizek and Johnson 2006; Handy and Xing

2011; Akar and Clifton 2010; dell'Olio et al. 2014; Stinson et al. 2014), as is the number of trips made by cyclists (Dill and Voros 2008; Stinson et al. 2014), though propensity and frequency should be modeled separately (Ma and Dill 2015). Xing et al. (2010) also found a correlation between the presence of infrastructure and the number of miles a cyclist will ride.

Time-based studies have been recommended by many to counteract the major flaw of cross-sectional studies in failing to identify time-based trends (Nelson and Allen 1997; Buehler and Pucher 2012; Dill and Carr 2003; Pucher et al. 2010). Repeated cross-sections have been conducted for major cities to measure bicycle commuting rates at two points in time (before and after infrastructure investments), with the hypothesis that the change in infrastructure availability will correlate with a change in cycling rates. Krizek et al. (2009a) used a repeated cross-section design with data from two consecutive decennial censuses to show that TAZs near new infrastructure showed increased cycling rates as compared to TAZs outside of the buffer zone. However, Cleaveland and Douma (2008) repeated similar methodology in six other major U.S. cities with varying effects. Parker et al. (2013) conducted an aggregated count-based study along a corridor in New Orleans before and after the implementation of a bike lane with two parallel control streets, showing that more users biked along the corridor after implementation. Some of the new users diverted from the control streets, though the scale was not large enough to truly assess the changes throughout the neighborhood.

Although repeated cross-sections are an improvement over the basic cross-sectional design, they still only allow for a limited temporal perspective, resulting in a need for experimental and quasi-experimental studies. Such studies employ surveys at two or more points in time to measure changes in preferences or behavior individually, as opposed to measuring two aggregate measures. In a truly experimental survey design, a sample of the population is randomly assigned to the treatment and control groups and intervention is administered to the treatment group. Differences in outcomes of the two groups can be evidence of a causal relationship between the intervention and the outcome. However, as Krizek et al. (2009b) point out, when studying the effect of bicycle infrastructure on bicycle ridership, it is not possible to randomly grant members of the population access to the intervention, as would be required in a true experimental design. Instead, quasi-experimental methods may be used where behavior of people in the community is measured before and after the intervention, controlling for factors other than the intervention that may influence the behavior. This behavior is then compared with behavior of residents from a community without a similar intervention, with all other measurable variables being as similar as possible.

Quasi-experimental research designs on this topic have been conducted sparsely. In fact, there are misconceptions about what constitutes a quasi-experimental design, with Mitra et al. (2016) calling a repeated cross section study quasi-experimental, and Heesch et al. (2016) calling a repeated cross section a "natural experiment". Heinen et al. (2015)

conducted a four-year quasi-experimental panel study for commuters living near a new multi-use path in England. This study found that commuters were likely to begin using nearby additional biking infrastructure for trips they already make. Although this disaggregate study was able to quantify use of the new facility, there was no control for users diverting from existing infrastructure, so it could explain only the overall trends in the neighborhood, without being able to separate the infrastructure effects from any other environmental effects. A similar study was performed by Song et al. (2017), also in the UK. Three waves of panel data were collected for residents near urban cycle facilities, with changes in socioeconomics also being included in modelling adoption. They found no general change in mode choice on the aggregate, but did find that those who did start using the infrastructure had significant mode shifts, particularly away from private automobile use. Sahlqvist et al. (2015) similarly conducted a panel survey for residents near multi-use paths in cities throughout the United Kingdom. They found that measures related to positive perceptions of walking and biking generally improved after the implementation of new infrastructure, though they lacked an analysis to describe differences in preferences. Rissell et al. (2015) performed a similar study in Australia, which used bike counts in addition to survey data, finding that bike counts after the treatment increased. However, the self-reported cycling rates did not change significantly, likely due to redirecting routes or by increased usage from individuals outside the study area. From these studies, it is clear that there is a need for more extensive studies of the quasi-experimental nature with the specific purpose of analyzing the effects of infrastructure on propensity to cycle, while using existing research as a basis of modeling parameters.

2.2 Data Sources

One challenge in determining the causal effect of infrastructure on bicycling behavior is the number of possible confounding variables, which requires collecting accurate data on many covariates, particularly from non-bicyclists. This section includes a summary of necessary data sources and potential collection methods.

Qualitative methods such as interviews and focus groups are critical to understanding infrastructure needs (Handy et al. 2014). These qualitative methods can support quantitative methods in important ways by suggesting new variables to be tested in a more rigorous quantitative methodology (Clifton and Handy 2003; Spencer et al. 2013). Focus groups can provide important insights into attitudes, perceptions, preconceptions and factors which might prompt changes in behavior. Variations in attitudes and behavior between rural, small town, suburban and urban settings can be difficult to understand without the more anecdotal and descriptive information obtained from focus group discussions.

Studies on recent increases in bicycling have included many different infrastructure treatments, programs, and policies. From a review of 139 separate studies, Handy et al. (2014) concluded that bike parking, integration with transit, cycling promotion programs, and combinations of multiple interventions have for the most part been associated with an increase in bicycling levels. Although the primary focus of this project is on the influence of cycling infrastructure on users' propensity to bike, the research design necessitates controlling for other known variables affecting cycling behavior to the extent possible.

Quantitative data is commonly obtained on the aggregate level from pre-existing sources such as the Census, American Community Survey (ACS), or National Household Travel Survey (NHTS), which allows for large-scale studies comparing different geographic areas (Krizek et al. 2009b; Buehler and Pucher 2012; Cleaveland and Douma 2008; Dill and Carr 2003; Jones 2012; Schoner and Levinson 2014; Stinson et al. 2014; Parkin et al. 2008). Similar data sets are used abroad, such as the National Travel Survey in Denmark (Nielsen et al. 2018) and the Bicycle Ridership survey in Canada (Cabral et al. 2018). These types of data sets have been used for cross-sectional and repeated cross-sectional designs, though they cannot be used to describe the changes of an individual based on treatment. For this, and other reasons, Cabral et al. (2018) demonstrate the using exclusively public data falls short of the mark.

Time-series data is difficult to collect, particularly on the disaggregate level, because it requires substantial, consistent data collection over a sustained period of time (Nelson and Allen 1997). However, this type of data is necessary for a quasi-experimental design and the associated implications of causality.

Researchers have typically used surveys as the primary data collection instrument for panel studies. Intercept surveys can be used to collect data from bicyclists (Thakuriah et al. 2012; Mitra et al. 2016), though other methods would be necessary to capture non-cyclists. Xing and Handy (2014) warn that the survey platform itself may influence the representativeness of the sample. In addition, Forsyth et al. (2010) point out that surveying a truly representative bicyclist sample is expensive, with many opting for surveys targeting cyclists, which may lead to results that are not representative of the population in general.

Although actual cycling rates are the ideal data source, there is also value in collecting data on stated preferences. This is often accomplished by presenting respondents with hypothetical bicycle infrastructure and recording responses. Sanders (2014) used digitally manipulated images to show to respondents. The benefit of these manipulations are the ability for researchers to isolate small changes while keeping the rest of the environment the same. Since then, others have used images in their surveys (Ghekiere et al. 2018: Abadi and Hurwitz 2018; Mertens et al. 2016). Griswold et al (2018) similarly used videos embedded in the survey to produce an added level of relatability. Although more advanced forms of media allow for more realistic experiences of the respondent, these methods require specialized survey mediums, which may limit the ability to obtain a representative sample.

Even more advanced data sources have also been utilized. Blanc and Figliozzi (2016) employ crowdsourced data and an app to gather self-reported measures of cyclists comfort. Oh et al. (2017) use an instrumented bike data to estimate objective cyclist comfort rather than stated or perceived comfort. Marqués et al. (2015) even use bikeshare data to estimate overall bike ridership data.

2.3 Types of Cycling Infrastructure

Studies of infrastructure treatments such as bicycle lanes, shared lanes, off-street paths, bicycle boulevards, cycletracks, bike boxes, traffic signal phases, traffic calming, car-free zones, and complete streets show that a significant increase in the number of bicyclists can be achieved by providing facilities for safe riding (Pucher et al. 2010).

As discussed by Handy et al. (2014), studies often measure infrastructure in simplistic terms such as miles of bicycle lanes or of all types of bicycle facilities without differentiation of facility type (e.g. Dill and Carr 2003; Krizek et al. 2009a; Cleaveland and Douma 2008; Schoner and Levinson 2014). Parker et al. (2013) found that implementation of a bike lane was effective in attracting bike trips to the corridor, while other studies have shown increased usage for on off-street bicycle and multi-use paths, though the magnitude differs in each case (Jones 2012; Heinen et al. 2015; Downward and Rasciute 2015; Rissel et al. 2015; Sahlqvist 2015).

Results regarding the relative impact on different infrastructure types are inconsistent. Buehler and Pucher (2012) find no significant difference between the effects of on-street bike lanes and off-street trails in cities throughout the United States, though both have a positive correlation with cycling. Hankey et al. (2012) found that off-street trails have a significantly greater impact on cycling than on-street lanes on the aggregate in Minneapolis, though Krizek and Johnson (2006) find a significant impact from on-street lanes, but not off-street trails on the disaggregate. Dill and Voros (2008) did not find sufficient evidence of objective measures of either on-street or off-street facilities in Portland, though perceptions of the availability of the infrastructure was significant. Moudon et al. (2005) also show a strong correlation for trails, but not for on-street facilities.

Research on the effects of bicycle boulevards—low traffic streets with provisions to give bicycles priority over motorists—is limited. Dill et al. (2014a) analyze the effects of bicycle boulevards in neighborhoods throughout Portland, OR with the intention of measuring change in active transportation levels, but are inconclusive in their analysis. More research is necessary for this infrastructure type.

Objective measures of infrastructure supply include facility density and distance to facility (Stinson et al. 2014; Dill and Voros 2008). Ma and Dill (2015) also used subjective measures based on how users perceive the availability of cycling infrastructure. Schoner and Levinson (2014) evaluate the connectivity of the infrastructure. They find that network discontinuities can discourage cycling by potentially forcing cyclists into mixed traffic or onto lengthy detours. Dill (2004) analyzed the correlation between four measures (street network density, connected node ratio, intersection density, and link-node ratio) to measure connectivity. Cyclist comfort levels are often influenced by discontinuities in a cycling network, reducing the overall utility of the facility (Krizek and Roland 2005). Moudon et al. (2005) found no correlation between measures of connectivity and cycling rates.

Dill and Carr (2003) find that while total availability of infrastructure is correlated with cycling rates, infrastructure alone is not likely to increase cycling. Parkin et al. (2008) point out that reasonable increases in bicycle facilities alone generate only a modest increase in cycling rates, and that forecasts from different studies will vary based on approach type and other unmeasured differences in environments and culture. Ma and Dill (2015) also report that inconsistencies may be the result of the different interaction between objective and perceptive infrastructure measures, especially visibility (Ma and Dill 2015; Sahlqvist et al. 2015). Dill (2009) states that a "network of different types of infrastructure appears necessary to attract new people to bicycling. Simply adding bike lanes to all new major roads is unlikely to achieve high rates of bicycling." Protected infrastructure is usually the preferred choice, particularly through intersections (Burbidge and Shea 2018).

Dill and McNeil (2013) suggest that different segments of rider types have different preferences. They segment the population into four different cyclist types based on confidence level: strong and fearless, enthused and confident, interested but concerned, and no way, no how. They identify the “interested but concerned” group as the design individual, which consists of those who are curious about cycling, but are not comfortable in mixed traffic and will typically only cycle if adequate facilities are provided for their trip purposes. Handy et al. (2010) use a nested logit model to segregate potential users into four groups. These groups are defined by individuals who do not have a bike, have bike(s) but do not bike regularly, have bike(s) and are a regular transportation-oriented bicyclist, and have bike(s) and are a regular non-transportation-oriented bicyclist.

Further evidence on the relative effectiveness of different kinds of facilities (e.g. bike lanes vs. paths vs. cycle tracks) comes from studies of route choice. However, most of these studies generally measure the preferences of existing cyclists rather than the ability of such facilities to entice new cyclists (e.g. Broach et al. 2012). Studies of route preferences among potential cyclists are limited to stated-preference studies. The drawback is that results from stated-preference surveys do not necessarily predict behavior (Klobucar and Fricker 2007).

Results from stated preference studies indicate that potential users would be more likely to cycle with separated infrastructure (Parkin et al. 2008; dell'Olio et al. 2014). A stated-preference study in Canada found that users view cycling in mixed traffic as more onerous than in bike lanes or on bike paths, though less so for those with higher confidence levels (Hunt and Abraham 2007). Sanders (2014) used a stated-preference study to analyze the preferences of non-cyclists as well as current cyclists. Barrier-separated facilities were consistently identified by both groups as a comfortable alternative; striped bike lanes were generally viewed as beneficial because they provided predictability and legitimacy to cyclists, though they did not consistently increase perceived comfort. In a study investigating the factors associated with cyclists' choice between available facilities, Kang and Fricker (2013) found that off-street paths were more attractive than bike lanes, though Krizek and Johnson (2006) found that cyclists prefer on street bicycle lanes to off street trails. Streets with bike lanes were also found to be preferable as compared to streets without a bike lane or with on-street parking.

Although the type of infrastructure is an important factor, not all facilities of the same type are equally attractive to users; physical factors like urban form, slope, and connectivity to bikeable destinations influences usage, and should be considered when planning for new routes (Klobucar and Fricker 2007). A study using objective GPS data for cyclists in Graz, Austria found that actual cyclist routes differed from shortest routes by infrastructure availability, presence of flat and green areas, and absence of major roads and crossings (Krenn et al. 2014). Krizek et al. (2007) use data from an intercept study along an off-street path to find that proximity to a trail plays a significant role in propensity to use that facility, though the impact of distance varies according to trip purpose. Tilahun et al. (2006) found that cyclists are willing to travel up to twenty minutes longer to switch to off-street infrastructure. Stinson and Bhat (2005) find that experienced commuters are much more sensitive to travel time, and less-experienced cyclists are more sensitive to factors related to separation from automobiles.

In a study of 162 cyclists in Portland, Oregon, Dill et al. (2008) also used GPS data to compare chosen route against the shortest path. The studies included both utilitarian and recreational trips and participants were chosen through stratified sampling from respondents of an online survey. The demographic and personal characteristics used for stratification were cycling frequency, home location, age, and gender. The most important factor in choosing a route was stated to be minimum time followed by low traffic volume and presence of a bike lane. No significant relationship was found between route choice and slope. A comparison between shortest route and the actual route showed that people spent more time on bicycle facilities and low traffic streets than predicted by the shortest route and that the deviation from shortest route increased with length of trip.

Broach et al. (2010) extended the study by Dill et al. (2008) to develop a multivariate discrete choice model of bike route choice of cyclists in Portland to predict marginal utilities of different attributes—a model being incorporated into the Portland regional travel demand model. The path attributes used for the model were distance, slope, turns, traffic volume, signals and bike facility type. With all other parameters held constant, the log of distance was the most important factor in route choice, implying that for a short commute, a cyclist will be less willing to take the same detour as he/she would be if the commute was longer. Slopes and turns were negatively viewed, along with high vehicular traffic volumes. Traffic signals had a positive utility when the cross traffic was high, but had a disutility for low traffic streets. Bike boulevards and paths were strongly preferred while the utility associated with bike lanes was just enough to offset the disutility of traffic volume in that link. Therefore, bike lanes are preferred in streets with high traffic, but they do not add any separate value to the cyclists by themselves. Although this study has a solid methodology, the results may not be applicable to places that lack the same bike infrastructure as Portland. It also fails to differentiate between different types of cyclists in the analysis, which has been shown to have an impact on route choice (Pucher and Buehler 2008).

2.4 Individual Factors

As mentioned previously, many studies on cycling behavior have been quantitative, but qualitative studies can provide important additions to current understanding. Qualitative studies have investigated attitudes toward cycling, influence of social groups, role of families and friends, and the contribution of childhood cycling experiences (Bonham and Wilson 2012; Lanzendorf 2003; Chatterjee et al. 2013; Aldred 2013; Bonham and Koth 2010; Daley and Rissel 2011; Steinbach et al. 2011; Underwood et al. 2014; Emond and Handy 2012). Such studies help to identify important factors not typically included in surveys and can aid in survey design and interpretation of results. They can also provide important insights into the thought processes underlying the travel choices that individuals make. This section includes a summary of measures relating to propensity to cycle on an individual level.

Studies have consistently shown that males are more likely to cycle (Krizek and Johnson 2006; Akar and Clifton 2010; Stinson et al. 2015; Parker et al. 2008; Handy and Xing 2011; Xing et al. 2010; Handy et al. 2010; Dill and Gliebe 2008; Cervero and Duncan 2003). Emond et al. (2009) used data collected in medium-sized cities throughout the western United States to analyze the gender differences in cycling behavior in the United States—differences that aren't as pronounced in other parts of the world. They report that for women, age is significant, along with comfort and an expressed need for a car, but not for men. Cycling as a youth and residential self-selection were more significant for men. Teschke et al. (2017) find that men are overrepresented among bike commuters, but in census tracts where bike mode share was greater than 7% the split between genders is closer to even. Aldred et al. (2017) discuss that although men and women have similar preferences for bicycle infrastructure, there is strong evidence that the magnitude of these preferences between the two groups are different, indicating a need to design for the stronger preferences of the underrepresented group.

Age is also an important factor in an individual's decision to cycle (Krizek and Johnson 2006; Hankey et al. 2012; Stinson et al. 2014; Parker et al. 2008; Xing et al. 2010; Handy et al. 2010). Hankey et al. (2012) found that the percentage of residents in a community below the age of 5 and above the age of 65 has a negative correlation with cycling. Stinson et al. (2014) found that individuals have a lower propensity to cycle for recreation the older they get after age 44. The frequency of recreational trips is at a minimum for individuals in their 40s, with those that are younger and older tending to take more trips. Handy et al. (2010) found that age is negatively correlated with bicycle ownership and use, while Xing et al. (2010) found a positive correlation with weekly miles of recreational biking.

Education level is positively correlated with cycling on the disaggregate as well as the aggregate level (Hankey et al. 2012; Krizek and Johnson 2006; Stinson et al. 2015; Emond et al. 2009). Employment status (Krizek and Johnson 2006) and hours spent at work have also been presented as significant factors (Moudon et al. 2005). The effects of income are still under debate. Krizek and Johnson (2006) found an inverse relationship. Stinson et al. (2015) also found an inverse, though weak, relationship. Handy and Xing (2011) found that age, income, and education level were not significant on their own, though homeownership is, which could serve as a proxy for the combined effects of all three. Emond et al. (2009) also found a negative correlation between home ownership and cycling. College students are also more likely to cycle (Akar and Clifton 2010; Nelson and Allen 1997).

Vehicle ownership has been shown to be negatively correlated with cycling commuting (Buehler and Pucher 2012; Dill and Carr 2003; Cervero and Duncan 2003). Conversely, Moudon et al. (2005) found that in the Seattle area individuals in households with more than one vehicle were more likely to cycle, though those trips were mostly recreation trips and vehicle ownership was likely a proxy for income. The nature of the interaction between vehicle ownership, income, and cycling is unclear. Handy and Xing (2011) also identify other important attitudes related to mode preference, such as biking comfort, liking biking, needing a car, limiting driving, liking transit, the need to run errands on the commute, the need to drive, and a preference of living in a bikable community.

Parkin et al. (2008) point out that ethnic origin is likely a contributor based on its representation of different cultures that may influence cycling behavior. Hankey et al. (2012) found that whites are less likely to cycle. However, Parker et al. (2013) found ethnicity insignificant as a predictor of changing behavior based on infrastructure investments.

Stinson et al. (2015) and Krizek and Johnson (2006) found that the number of children in the household were associated with more cycling, particularly for recreation.

Other individual factors include exercise habits (Moudon et al. 2005) and good health (Emond et al. 2009).

Bike ownership has been shown to be a significant enabling factor (Moudon et al. 2005; Akar and Clifton 2010; Krizek and Johnson 2006; Cervero and Duncan 2003). Handy et al. (2010) further analyzes the predictors of bicycle ownership, suggesting the improving people's perceptions and attitudes towards biking will increase bicycle ownership and use.

In a study by Fernandez et al. (2014) regarding attitudes towards cycling, four latent variables are identified: pro-bike, physical determinants, convenience, and exogenous restrictions. Convenience, measured by efficiency and flexibility, along with exogenous restrictions, measured by danger and available facilities, are the most important elements regarding attitudes for cycling. Emond et al. (2009) also find that liking cycling increased propensity to cycle, while liking transit and the perception that cyclists are poor are negatively associated with cycling.

2.5 Taste Variations

Aside from safety in numbers, there are other reasons for which recruiting more cyclists would be beneficial for communities. Aldred et al. (2017) summarize that, in places where bicycling is not common, certain groups of people (namely women and older individuals) are typically underrepresented among cyclists, evidence that existing bicycle infrastructure may be unsuitable for the tastes of these groups. They find that, while no measurable group prefers mixed-traffic bicycling to separated infrastructure, the preferences for separated infrastructure are reported to be stronger for these underrepresented groups. Additionally, Misra and Watkins (2018) used GPS route choice data to confirm that revealed preferences for certain roadways differ by age and gender. For municipalities seeking to improve the quality and suitability of bicycle facilities, it is important to identify and quantify differences in preferences and perceptions among individuals. Doing so has the potential to permit more accurate assessments of the market of potential cyclists that may be inclined to begin biking or increase biking based on the introduction of certain infrastructure characteristics. Furthermore, the non-representativeness of current bicyclists in comparison with the population in many communities indicates that substantial portions of these groups may be indirectly excluded by failing to document how the preferences of these individuals differ from the rest of the population. Many others have also investigated the role of sociodemographics in bicycling facilities preferences (Branion-Calles et al. 2019; Parkin et al. 2008) though these characteristics are typically applied only in a general sense, identifying an average effect rather than identifying how these characteristics may shape preferences. Handy and Xing (2011) were among the first to demonstrate the impact of attitudes such as liking biking on the likelihood of bike commuting. However, their analysis was also limited by the fact that they only explored the role of attitudes as explanatory variables and not as key indicators for class segmentation.

There are a variety of ways to account for the heterogeneity of preferences and perceptions among different groups (Rossetti et al. 2018). Félix et al. (2017) discussed some of these modeling strategies, including segmented models and latent-class models. They found that most useful segmentations include classes similar to the following: proficient riders, willing but not convinced, and noncyclists. Clark et al. (2019), along with Sanders and Judelman (2018), use bicycling frequency to determine segments. Geller (2006) along with Dill and McNeil (2013) segmented the population into four different cyclist types based on confidence level: strong and fearless, enthused and confident, interested but concerned, and no way, no how. Handy et al. (2010) segregate based on both bike ownership and bicycling frequency.

Wang and Akar (2018) were among the first to incorporate preferences regarding other modes into their class assignment in addition to frequency, by splitting the “non-cyclist” segment into a segment that is pro-drive and another segment that is pro-transit and pro-walking. However, these segments were only applied to perceptions of bicycling intersection safety, and determination of segments was made based on present mode choice rather than attitudes.

There are a variety of ways to control for the heterogeneity of preferences and perceptions among different groups (Rossetti et al. 2018). Félix et al. (2017) discuss some of these modeling strategies, including segmented models and latent class models. In a review of the literature, they find that researchers assign class or segment membership through expert judgment, rule-based criteria, self-decision, cluster analysis, and factor analysis. They identify several useful criteria for segmentation: experience, confidence, cycling frequency, trip purpose, reactions to weather, comfort, ability, age, job, bike ownership, risk perception and gender. Félix et al. (2017) find most useful segmentations include classes similar to the following: proficient riders, willing but not convinced, and noncyclists. Sanders and Judelman (2018) use frequency-based segments of never, rare, occasional, and frequent. Wang and Akar (2018) use attitudinal and frequency-based classes of regular cyclist, potential cyclist, pro-drive non-cyclists, and pro-walk non-cyclists.

2.6 Trip Purpose

The needs, behaviors, and preferences of cyclists may vary based on trip type. It is likely that trip purpose plays at least a small part in explaining inconsistencies between studies in this regard. Many studies only consider commute trips due to the ease of obtaining aggregate commuting data, which may miss valuable data from other trip purposes (e.g. Krizek et al. 2009a; Cleaveland and Douma 2008; Buehler and Pucher 2012; Dill and Carr 2003; Nelson and Allen 1997; Jones 2012; Parkin et al. 2008). Others build disaggregate bicycle commute mode choice models (dell'Olio et al 2014; Handy and Xing 2011). Some studies account for all trip types with no specification of purpose (Hankey et al. 2012; Parker et al 2013; Heinen et al 2015). Other studies account for differences in behavior between commuting/utilitarian trips and recreational trips and models include separate considerations for each (Stinson et al 2014; Dill and Voros 2008; Xing et al. 2010). Buehler and Pucher (2008) suggest that separate facilities along utilitarian routes will see more use than recreational routes.

Heinen et al. (2013) investigated the correlation of work-related factors in the Netherlands and the decision to cycle to work and the frequency of bicycle commuting. Positive attitude towards cycling, colleagues' expectations of cycling to work, bike storage, changing facility, and needing a bicycle during office hours were positively associated with the decision to cycle to work, while facilities for other modes, commute distance, and the need to transport goods were negatively correlated. Frequency of commuting was negatively affected by distance and the provision of either a transit pass or free automobile parking.

Buehler (2012) likewise examined the role of bicycle parking, cyclist showers, free car parking and transit benefits in the Washington, D.C. Metro Area. Presence of bike parking, showers, and lockers was significantly associated with higher propensity to cycle, while free car parking and high vehicle ownership reduced it. Car parking and other facilities at work are also addressed by Heinen et al. (2015) and Heinen et al. (2013).

Kroesen and Handy (2014) use data from a Dutch mobility panel to analyze factors relating to behavior of four groups: non-cyclists, non-work cyclists, all-around cyclists, and commuter cyclists. All-around cyclists are the most stable in their behaviors, so efforts to increase users in that type will lead to the most stable patterns. Factors that encourage more cycling to work may also have a positive effect on non-work trips (Kroesen and Handy 2014). However, the experience in the Netherlands may not be consistent to that of the United States.

2.7 Environmental Factors

Many of the best studies to date have been conducted in locations with very different land use and transportation policies. Studies in communities where cycling is still emerging and community acceptance is moderate have been limited, though example studies include Los Angeles (Stinson et al. 2014), New Orleans (Parker et al. 2015), and Edmonton, CA (Cabral et al. 2018). For results from one specific location to be generalizable, the environmental factors must be considered.

Weather has been found to be significant on an aggregate level in multiple studies. Dell'Olio et al. (2014) account for the presence of bad weather for an individual's trip, while other studies include more objective data to assess weather conditions. Variables measuring weather that have been significant include number of days above 90 degrees F (Buehler and Pucher 2012), annual precipitation (Buehler and Pucher 2012; Parkin et al. 2008), days of precipitation (Dill and Carr 2003, Nelson and Allen 1997), mean high temperature (Nelson and Allen 1997), and mean temperature (Parkin et al. 2008).

Urban form appears to be significant in multiple studies. A study in the Netherlands found a significant influence of urban form on trip length and cycling rates (Susilo and Maat 2007). Other variables that have been shown as significant in the United States on the aggregate level include sprawl index (Buehler and Pucher 2012), tract characteristics (Stinson et al. 2014), and population density (Parkin et al. 2008; Pucher and Buehler 2006). On the disaggregate, proximity to freeways and distance from downtown are both deterrents (Dill and Voros 2008), while subjective/perceptive variables (Moudon et al. 2005), settlement size (Heinen 2015), and transit availability (Handy and Xing 2011; Xing et al. 2010; Handy et al. 2010) are also influential. Conversely, Cervero and Duncan (2003) found impacts of the built environment to be marginal, though darkness was a major deterrent.

Cole-Hunter et al. (2015) performed a study identifying environmental factors in Barcelona pertaining separately to home, work, and route. They found that vegetation along the route is associated with more cycling, while changes in elevation are associated with less cycling (Cole-Hunter et al. 2015). Holle et al. (2014) conducted a stated-preference survey and found that vegetation can make cycling infrastructure more inviting to cyclists and non-cyclists. Slope and elevation differences have also been identified as deterrents to cycling (Nelson and Allen 1997; Parkin et al. 2008; Dill and Voros 2008; Cole-Hunter et al. 2015).

Dill et al. (2014b) suggest that the built environment impacts cycling behavior through its effects on attitudes and perceived behavioral control. Bicycle infrastructure can likely have an effect in that way, though other aspects of the built environment have a different effect; adding bike lanes to an otherwise poor cycling environment may not provide an increase in usage. In Santiago, Chile, Oliva et al. (2018) find that higher cycling rates are associated with lower transit accessibility, which may be an indication of mode-captive users.

2.8 Policy and Cultural Factors

Policy and activist groups have had significant influence in the past for both encouraging cycling and lobbying for more facilities in Davis, CA (Buehler and Handy 2008). Residents lobbied heavily for facilities in Davis beginning in the 1960s. Facilities came as a result of advocacy groups and policies and the cycling culture developed. However, cycling rates have been decreasing since 1990, accompanying changing demographics, intercity commuting, and increased transit. Programs and system expansion have ceased, likely leading to a deterioration in cycling culture (Buehler and Handy 2008).

Caulfield (2014) addressed the conglomerated effects of infrastructure investments and other programs on the aggregate in Dublin. Programs include financial incentives, promotion, bike share, and political support. The combination of these produced an increase in commute mode share from 2006-2011, though it is recommended that targeted policies be adopted to reach those on the verge of switching to cycling. Programs and other policies that often accompany infrastructure investments are also expected to increase cycling (Caulfield 2014), so it is difficult to quantify and disentangle the effects of "hard" and "soft" interventions. In Boulder, CO after nearly $100 million worth of investments in bike, pedestrian, and transit infrastructure between 1990 and 2009, it was estimated that each $10 million invested corresponded to a 1% increase for alternative modes (Henao et al. 2015). The Nonmotorized Transportation Pilot Program (NTPP) was developed by the Federal Highway Association (FHWA) in an effort to assess the cost-effectiveness of different strategies in increasing nonmotorized mode shares. Each of the four pilot communities (Columbia, MO; Minneapolis, MN; Sheboygan County, WI; Marin County, CA) saw a significant increase in nonmotorized travel over the course of the pilot from 2007 and 2010. It is not readily apparent whether the funding was provided in response to demand, or if the demand followed the funding (FHWA 2012).

Pucher and Buehler (2008) suggest that the difference between cycling levels in the United States and European countries is primarily due to policy differences, though infrastructure and other factors likely play a role. Ogilvie et al. (2007) also find that targeted behavior change programs were the most effective. Pucher and Buehler (2006) studied the differences between Canada and the United States to explain factors that influence the higher cycling rates in Canada. They find that the high cost of vehicle ownership along with pro-cycling policies and programs in Canada are significant factors promoting cycling.

In a study comparing cycling throughout Europe, Rietveld and Daniel (2004) identify a cultural tradition that may play a significant role in the individual decision to cycle that could even be stronger than other characteristics. Chataway et al. (2014) compared cyclist behaviors and attitudes between Brisbane, Australia (an emerging cycling city) and Copenhagen, Denmark (an established cycling city). They found that users in the less-established cycling city were more uncomfortable in mixed traffic and felt more fear of traffic, making them more likely to avoid cycling.

Attitudes about cycling can be a treacherous issue to tackle, as emotions can flair high. Kaplan and Prato (2016) use talk-back thematic analysis, or a review of public comments to online news articles, to identify perceptions of cycling in general. They found that many comments were emotionally charged, with those who are anti-cycling expressing questions of the legal rights to the road, while those who were pro-cycling were focused on the lack of cycling infrastructure. Piatkowski et al. (2017) identify behavioral patterns of interactions between automobile users and cyclists, finding that drivers behave in a way to enforce their perceived norms, based on personal experience rather than standardized and existing laws. Thompson et al. (2017) further corroborate these findings and suggest that in order for engineering solutions to change this dangerous dynamic, bicycle facilities must physically separate cyclists from motorists. Correlation has been established between cycling rates and safety (Pucher and Buehler 2006; Buehler and Pucher 2012) so measures that improve the safety of the cycling environment can jointly serve both interests by also encouraging cycling. A more comprehensive analysis of bicycle safety was performed by DiGioia et al (2017).

2.9 Summary

Although there has been much work to study the needs and preferences of cyclists, there is an alarming shortage of research involving current and potential cyclists from places in the U.S. that are more representative of the typical cycling scene. The few studies that do explore stated preferences from the general population do not link these preferences back to characteristics about the type of cyclists. The research conducted in this thesis seeks to confirm findings from studies conducted in cycling hubs, along with explaining the differences in preferences among different types of cyclists.

CHAPTER 3. SURVEY METHODOLOGY DESCRIPTION

This chapter includes a description of the survey methodology and demographics of the sample and population. This survey development and data collection in Anniston, Opelika, Chattanooga, Talladega, Northport, and Birmingham, as well as the initial analysis and application for bicycle infrastructure planners was funded by the National Cooperative Highway Research Program (NCHRP), the research arm of the Transportation Research Board of the National Academies. A supplemental addition was sponsored by the Georgia Department of Transportation (GDOT) with data collection in the Atlanta neighborhoods of Eastside, Westside, Grant Park, and South Atlanta. For the descriptive purposes of this chapter, the datasets will be combined.

3.1 Selection of Communities

The choice of the specific areas of study was driven by the timelines of the new bike infrastructure projects, and the expected date of entry into service of the newly built infrastructure. Ten neighborhoods (study areas) were ultimately included in the study. Six neighborhoods were initially chosen, of which three neighborhoods were defined as “treatment” neighborhoods, as each had plans for new bicycle infrastructure to open between Fall 2016 and Fall 2017, and three neighborhoods were defined as “control” neighborhoods, which had similar demographics and land use characteristics as the treatment neighborhoods but had no such plans to open bike infrastructure over the same timeframe.

Study sites were selected from candidates in Alabama, Georgia, and Tennessee, where cycling for transportation is relatively new and rapidly expanding. This is in contrast to previous research on preference of bike facilities that has predominantly been conducted in communities where cycling is widely accepted and automobile drivers are conditioned to the presence of cyclists. The three project sites include:

- Opelika, Alabama: roadway diets and bike lanes
- Chattanooga, Tennessee: bike lanes
- Anniston, Alabama: downtown sharrow network

Control neighborhoods were chosen so that each treatment neighborhood could be paired with a control neighborhood in terms of land-use and sociodemographic characteristics. Birmingham, AL was chosen as a control for Chattanooga, while

Talladega, AL was chosen for a control for Anniston and Northport, AL for Opelika. The initial six study neighborhoods are shown in Figure 3-1.

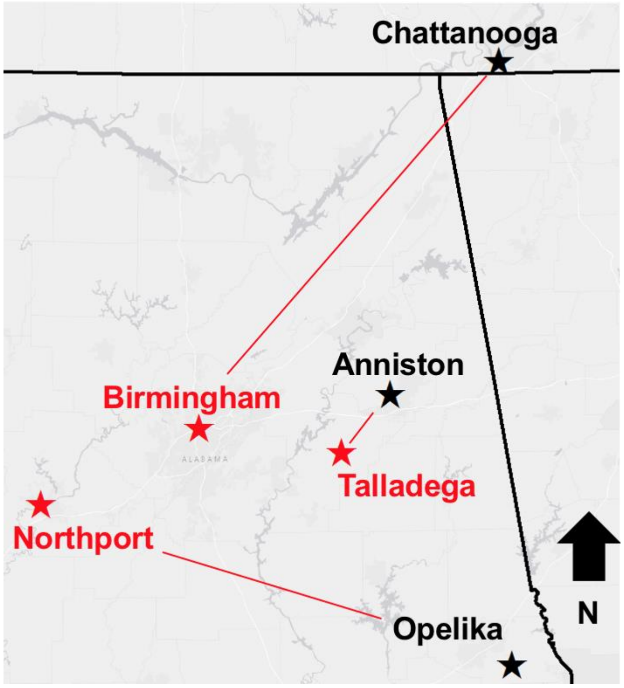


Figure 3-1 Map of treatment neighborhoods (black) and their control neighborhood pairs (red).

The sites added to the research effort through the supplemental funding from GDOT were part of the BeltLine corridor, a multi-phase project to ultimately connect a 22-mile ring of multi-use paths around the city of Atlanta. Two extensions were planned over the course of the study period: The Eastside Extension and The Westside Trail. Treatment areas were defined by areas without a half mile buffer of the proposed extensions (limited by physical barriers such as a freeway with no bicycle facilities crossing the barrier). Control sites were chosen from neighboring communities in Grant Park and South Atlanta, which in turn, are expected to receive their own BeltLine segments within the next 5-10 years. A map of these communities is presented in Figure 3-2. Sociodemographics comparing each study site with their control are presented in Table 3-1.

Figure 3-2 Map of treatment and control BeltLine neighborhoods.

Table 3-1 Sociodemographics for Treatment and Control Neighborhoods

	Age				Race / Ethnicity		
Site	18-34	35-49	50-64	65+	White / Caucasian	Black / African American	Other*
Anniston	29%	21%	30%	20%	36%	61%	5%
Talladega	32%	25%	26%	17%	40%	57%	11%
Opelika	30%	22%	28%	20%	45%	51%	8%
Northport	40%	18%	21%	20%	56%	39%	9%
Chattanooga	46%	21%	21%	12%	43%	52%	11%
Birmingham	52%	19%	17%	11%	41%	53%	11%
Eastside	49%	28%	16%	7%	55%	36%	13%
Grant Park	42%	33%	18%	7%	58%	36%	12%
Westside	30%	29%	26%	16%	5%	93%	4%
South Atlanta	39%	30%	22%	9%	19%	71%	21%

* "Other" includes "Hispanic", which is not mutually exclusive from other categories and also allows for a person to be identified as more than one race/ethnicity; totals may exceed 100%.

3.2 Survey Method

The initial sample of respondents invited to complete the first wave survey was built with a *stratified random sampling* methodology. The "treatment" neighborhoods included residents within a radius of 0.5 mile to 1 mile from the location of the coming new bike infrastructure. For the "control" neighborhoods, similar-sized areas to the treatments were considered, matched on key variables, including population and employment density, income, household size, race and ethnicity, and presence of student population. These comparisons were done using American Community Survey (ACS) data and verified using demographic data purchased with the addresses from the targeted marketing company. Additional consideration was given to characteristics of regional and local transportation accessibility, e.g. proximity to a freeway or other major highways, access to transit, and existing bike network.

The intent of the survey was (1) to identify the composition of the population of current and potential bicycle users, and their characteristics, (2) to assess the size of the persuadable market of potential bicycle users, and (3) to assess preferences for "treatments", e.g. different types of bicycle infrastructure and facilities. Questions were designed to address these purposes.

3.3 First-wave Survey Design

The survey was designed through an extensive process of writing, debating, and rewriting over a six-month period to identify and refine survey questions. The goal was to produce a survey instrument that took approximately 30 minutes to complete. This allowed balance between obtaining a thorough set of variables and limiting the time commitment from participants. To reduce potential response biases, the content of the survey was purposefully broader than just cycling to help ensure that participants remained interested and did not quit the survey if they did not recognize themselves as the "biking type". To the extent practical, questions were reused from previous surveys, both to rely on previously tested and vetted questions and to maximize opportunities for cross-study comparisons of results. The resulting survey contains six sections, including:

A. Attitudes

B. Technology usage

C. Home

D. Daily travel

E. Bicycling experience

F. Demographics

The complete survey instrument is found in Appendix A.

3.4 Infrastructure Images

The primary method for measuring perceptions and preferences in this survey was the presentation of manipulated images created in Adobe Photoshop. One common roadway setting was chosen as a base image to control for urban environment, weather, and other contextual variables. Variations were made based on different types of bicycle infrastructure, the presence or absence of on-street parking, and the number of automobile lanes. Each scenario exhibited a moderate amount of automobile traffic that would allow for near-free flow conditions along with a reasonable amount of opportunity for auto-to-cyclist interactions. The images were designed such that the background scenery would be recognizable by urban dwellers as an in-town neighborhood and rural dwellers as a small town.

Sixteen images of on-street infrastructure were prepared, shown in Figure 3-3. For each of the four base lane configurations (2 lanes with parking, 2 lanes without parking, 4 lanes with parking, 4 lanes without parking) images were prepared with each type of bike facility, including sharrows, bike lanes, buffered bike lanes, and barrier-protected bike lanes (also referred to as separated bike lanes or cycletracks). Two of the protected bike lanes were one-way, while the other two were two-way. An image for a multi-use path was also created, shown in Figure 3-4, though due to the nature of this type of infrastructure a different road environment had to be used.

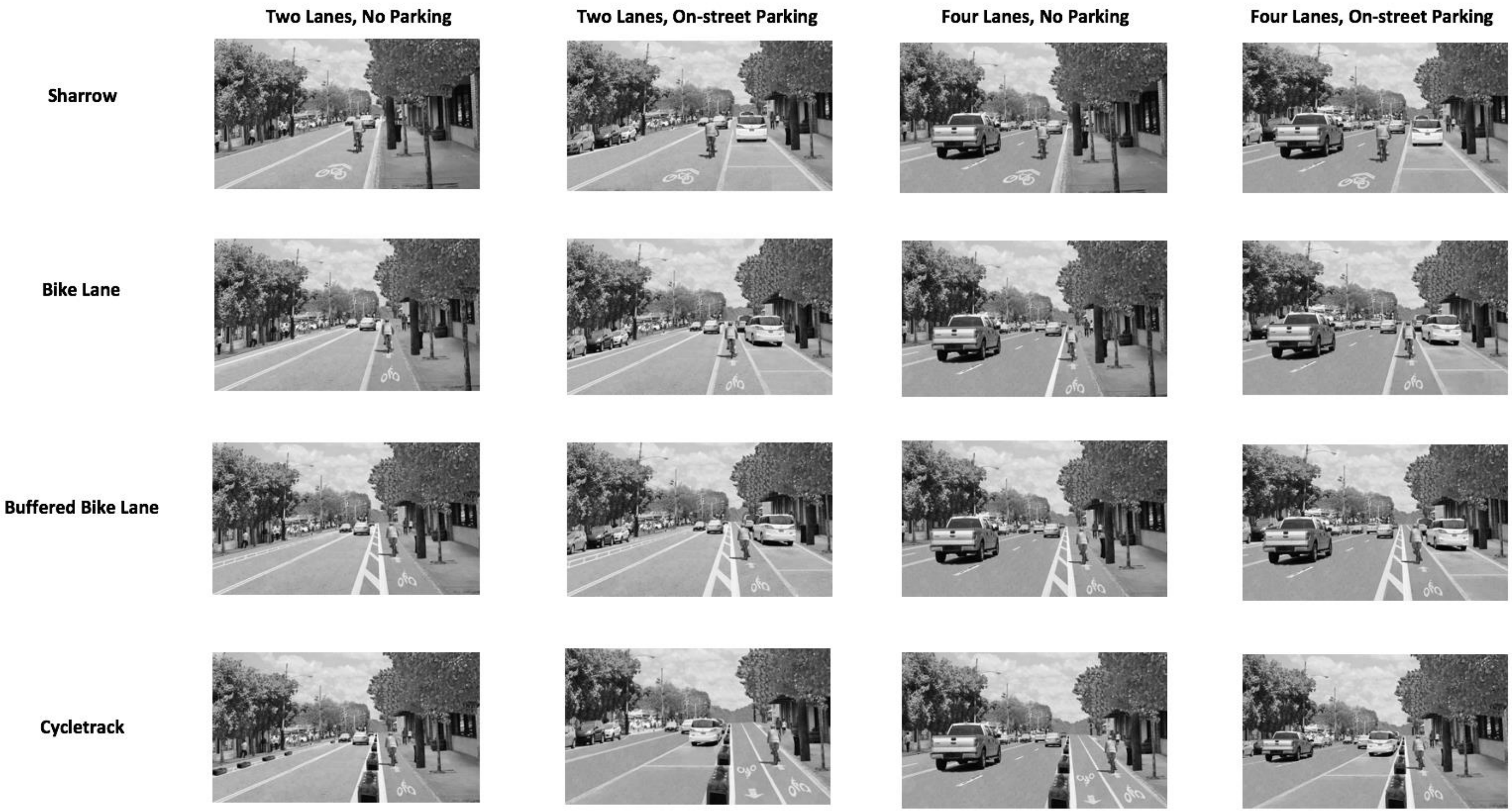


Figure 3-3 Images of Infrastructure Configurations for Different Roadway Layouts Used in Survey.

Figure 3-4 Image for Multi-use Paths Used in Survey

For each image, respondents were given the prompt: “Bicycling on a road [trail] like this is…”. They were presented with a 5-point Likert-type scale (Strongly disagree, Disagree, Neutral or No opinion, Agree, or Strongly agree) and asked to choose the response most appropriate for each of three perceptions: “Comfortable”, “Safe”, and “Something I’d try”.

To avoid survey fatigue, each respondent was only shown six of the images. Four versions of the survey were designed to ensure that all images were represented by at least a fourth of the sample. Respondents were randomly assigned one of four versions, each of which had a base road configuration (e.g., two lanes with on-street parking, or four lanes with no parking) for which a sequence of all four on-street infrastructure types were shown. Two other images were also included, from among the other road configurations and/or multi-use trails, so each respondent was presented with six infrastructure combinations, with several combinations being repeated between surveys to allow for greater cross-comparison. The distribution of images between survey versions is shown in Figure 3-5 and Figure 3-6.

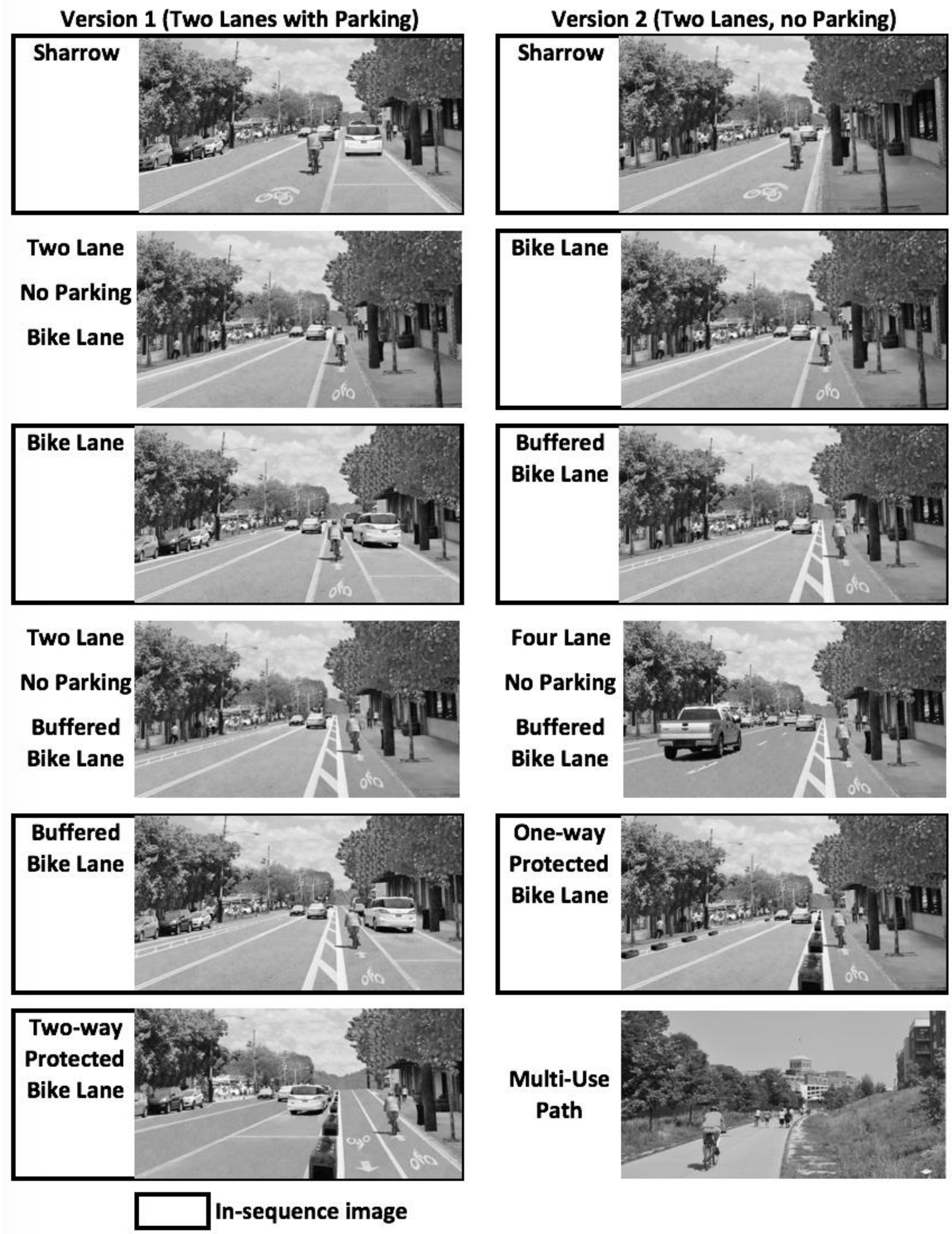


Figure 3-5 Combinations of bicycle infrastructure used in survey versions 1 and 2.

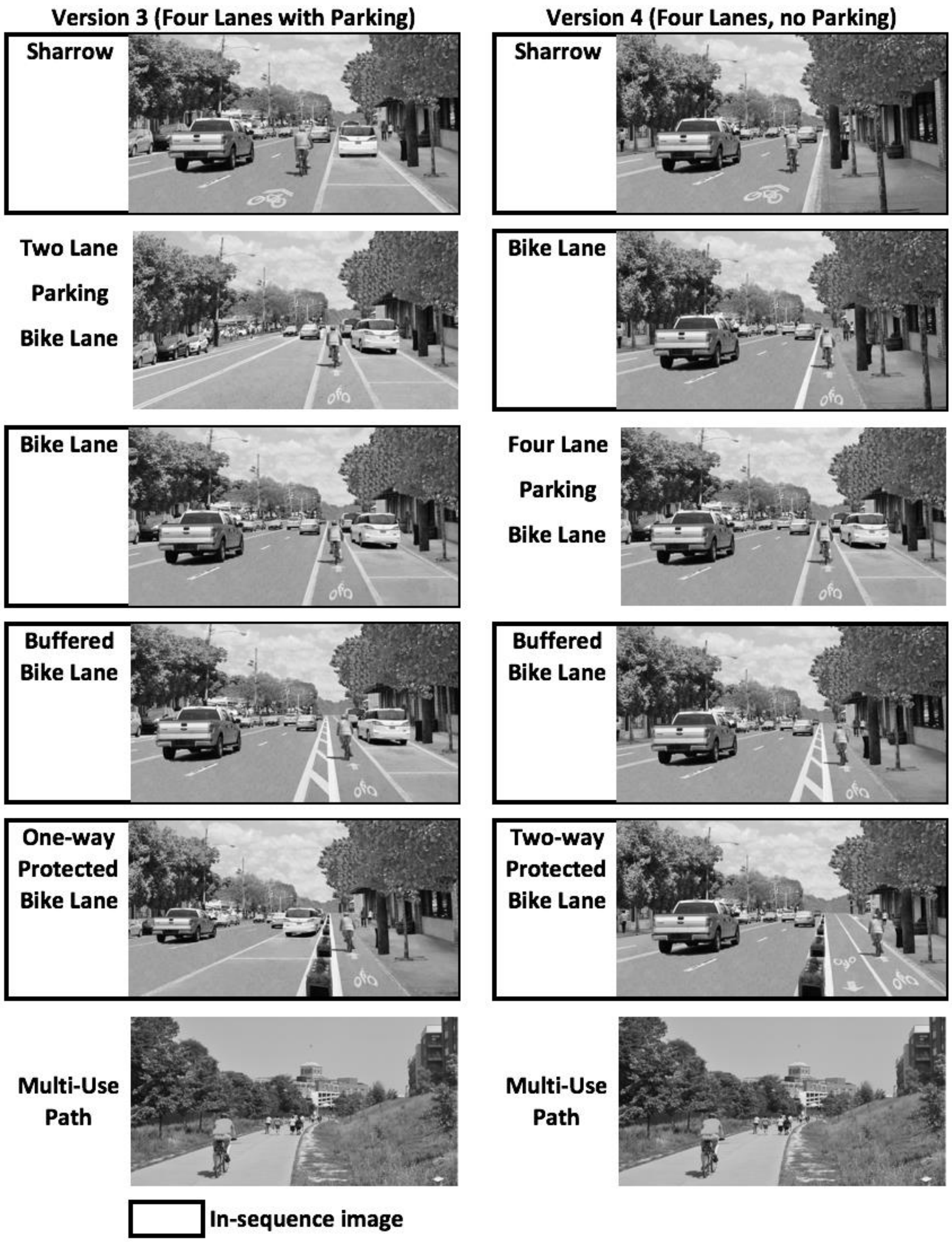


Figure 3-6 Combinations of bicycle infrastructure used in survey versions 3 and 4.

3.5 Second-wave Survey Design

The data collection with the second wave survey commenced in Spring 2018. All respondents who completed the first wave survey were invited to complete the follow-up second wave online or mail back survey. For the treatment communities, i.e. those undergoing the addition of new bicycle infrastructure, this served as the after survey, which was used to measure any changes in travel behavior reported after the opening of the new bicycle infrastructure planned in the area. For the other communities, the survey acted as a control for background changes in attitudes and demographics that may be confounded with the influence of the new infrastructure. This before-and-after-with-control-group approach is considered to be a robust quasi-experimental design that protects against a number of common threats to validity, providing strong evidence for the impacts of various infrastructure improvements on cycling behavior.

The structure of the second survey was similar to the first survey. The survey was shortened somewhat to ease the burden placed on the respondents, but many questions were repeated verbatim to provide identical measurements for two points of time. Examples include bicycling distances and frequency, from which changes in behavior can be inferred. Additionally, respondents were shown two new questions which asked for their perceptions and use of any new infrastructure improvements. These questions were designed to provide a measure of perceived changes that can be self-contained in the second wave. Both an online version and a paper version were prepared. The resulting survey (which can be found in Appendix B) was 9 pages, taking approximately 20 minutes to complete, and contained four sections, including:

A. Attitudes
B. Daily travel
C. Bicycling experience
D. Demographics

With the ever-changing nature of some transportation systems, it was desired to gauge the general perceptions of changes in transportation in each neighborhood, including for automobiles, transit, walking, and bicycling. A general question on perceptions of changes in transportation in the community was included to fulfill this purpose, with statements relating to perceived changes in quality of roadways, transit, bicycling, walking, and ridehailing. This also helped to avoid leading respondents about specific changes, and provided a reasonable basis for comparing perceptions of bicycle infrastructure.

The second-wave survey was deployed in May 2018 and responses were collected throughout the summer, with the exception of Chattanooga and Birmingham, where, due to delays in the Chattanooga projects of interest, the survey deployment was intentionally postponed until fall. The invitation list for the second-wave survey was composed of all respondents from the first wave. Respondents were again offered incentives of $2 bills for repeating this wave of the survey. Printed versions of the survey were mailed to all on the list. Additionally, email invitations with a URL to take the survey online were sent to all subjects who had provided an email address. As with the first-round survey, the research team provided a 1-800 number and email address to field questions or comments from respondents. Each paper survey was entered (coded) twice and the two datasets were compared to ensure no coding errors were introduced in the data-entry process.

3.6 Survey Response

The first-wave survey received 2,558 total responses and the second-wave survey received 1,296 responses, distributed by area as shown in Table 3-2. Although most neighborhoods received lower than the desired 10% response rate, this sample is large enough to have useable results from the survey in all areas. The results in Talladega are enough for a control area, although segmenting by demographics or other variables will be limited.

Table 3-2 Invitations and Responses for the First and Second Survey Waves

Area	Households Invited	Initial Responses	Initial Rate	Follow-up Responses	Follow-up Rate
Anniston*	4348	198	4.6%	98	49%
Opelika*	3363	185	5.5%	103	56%
Chattanooga*	4400	239	5.4%	85	36%
Talladega	3305	93	2.8%	47	51%
Northport	3708	234	6.3%	145	62%
Birmingham	4294	274	6.4%	105	38%
Eastside*	4,509	433	9.6%	231	53%
Grant Park	4,411	477	10.8%	265	56%
Westside*	5,035	235	4.7%	108	46%
South Atlanta	3,815	190	5.0%	109	57%
Total	41,118	2,558	6.2%	1,296	51%

*Indicates treatment location with planned bicycle facility improvements

3.7 Data Cleaning

A general screening and more in-depth review for missing data was utilized. Unfinished surveys and those with a low proportion of questions answered were removed entirely from the raw database. An additional assessment was undertaken on a section-by-section basis, using commonly accepted methods to fill in small amounts of missing data, and excluding cases with an unacceptable amount of missing data. Cases were evaluated for inclusion or imputation on different completion criteria for each section, as follows:

- Section A (Attitudes): Cases with more than five missing items (out of 38 in the section) were deleted, otherwise missing items were imputed using expectation maximization.
- Section B (Technology usage): Uncleaned to date
- Section C (Home): Uncleaned to date
- Section D (Daily travel): Logical variables were introduced to account for any discrepancies between employment data and commute pattern data.
- Section E (Bicycle experience): For key dependent variables and segmentation variables, all missing responses were excluded from the respective models.
- Section F (Demographics): Where available, responses with small amounts of missing sociodemographic data were supplemented with information from our targeted marketing database.

After cleaning, the raw database was consolidated into a working database of 2,513 respondents. Each person responded to 6 different images, so there were up to 15,078 image responses for each of the 4 questions (comfort, safety, willingness to try, and frequency), though responses were excluded from their respective models in cases of item non-response.

3.8 Factor Analysis

The first section of the survey contained 38 items involving general attitudes regarding transportation and other relevant topics, with response options constituting a five-point Likert-type scale from "strongly disagree" to "strongly agree". Respondents with more than five missing answers in this section were removed from the dataset, with any remaining item non-response being addressed through expectation-maximization imputation methods. The resulting sample was then analyzed using exploratory factor analysis. After multiple iterations, a final solution was identified. The full analysis, which can be found in NCHRP (2019), includes a rich set of 10 factors involving 28 of the 38 items, with the remaining 10 items either loading uniquely on one factor or weakly on many, and which were therefore removed from the common factor space. Not all 10 factors were used in this dissertation, so for the sake of brevity, the partial factor loading matrix (presented in Table 3-3) includes only the seven utilized factors and the items that loaded heavily (> 0.300 in magnitude) on them. The correlation matrix for these factors is presented in Table 3-4.

Table 3-3 Partial Pattern Loading Matrix for Factor Analysis

	Car Preference	Bike Enjoyment	Multi-modal	Utilitarian Travel	Anti-Exercise	Risk Tolerance	Cycling Rarity
Owning a car is an important sign of freedom	0.666						
I like traveling by car	0.620						
I am fine with not owning a car, as long as I can use/rent one any time I need it	-0.531						
Our first concern for transportation should be helping cars get around better	0.431						
I like bicycling		0.692					
I would bicycle more if my friends / family came with me		0.623					
I like the idea of sometimes walking or biking instead of taking the car		0.373					
Improving sidewalks should be a priority for my town			0.473				
I like using public transit when it provides good service			0.382				
This country has gone too far in its efforts to protect the environment			-0.374				
I like the idea of living in a neighborhood where I can walk to the grocery store			0.360				
I am trying to have an environmentally-friendly lifestyle			0.354				
The only good thing about traveling is arriving at your destination				0.675			
I generally enjoy the act of traveling itself				-0.321			
The importance of exercise is overrated					0.654		
Getting regular exercise is very important to me					-0.506		
Taking risks fits my personality						0.509	
I like trying things that are new and different						0.483	
Around here, adults who bicycle for transportation are viewed as odd							0.505
Most drivers don’t seem to notice bicyclists							0.346

Notes: Oblique rotation with regression factor score estimation was used. Loadings less than 0.3 in magnitude are suppressed for clarity.

Table 3-4 Correlation between Factors

	Car Preference	Bike Enjoyment	Multi-modal	Utilitarian Travel	Anti-Exercise	Risk Tolerance	Cycling Rarity
Car Preference	1.00	-0.14	-0.13	0.03	0.12	-0.02	-0.01
Bike Enjoyment		1.00	0.19	-0.02	-0.16	0.17	0.01
Multi-modal			1.00	-0.03	-0.11	0.09	-0.04
Utilitarian Travel				1.00	0.09	0.03	0.01
Anti-Exercise					1.00	-0.05	0.04
Risk Tolerance						1.00	0.01
Cycling Rarity							1.00

3.9 Combined Study Area First-wave Statistics

The purposes of this section are primarily to illustrate trends of demographics in the working database and to allow comparison to the populations to which the respondents belong. Note that in most cases the most appropriate comparison is 5-year 2014 ACS data at the block group level, but in others the Targeted Marketing Data (received from Direct Mail) from which the original addresses were obtained was used for comparison to the respondents.

Table 3-5, shows the respondents' household incomes and a comparison to the study area population household incomes. As is typical for self-administered surveys of the general population, the respondents tend to be wealthier than the study area populations.

Table 3-5 Survey Respondents' and Study Area Population Household Income (N=2,495)

Household Income	Responses	% of Respondents	% Respondents Answering Question	% Population from ACS
$15,000 or less	278	11%	13%	26%
$15,001 - $30,000	245	9.7%	11%	20%
$30,001 - $50,000	278	11%	13%	18%
$50,001 - $75,000	362	14%	17%	15%
$75,001 - $100,000	306	12%	14%	8.1%
$100,001 - $125,000	211	8.4%	9.6%	4.9%
More than $125,000	509	20%	23%	7.9%
Prefer not to answer	306	12%		

Table 3-6 shows the respondents' household sizes and a comparison to the study area population household sizes. Inspection of the data indicates that fewer one-person households responded, while more two-person households responded to the survey.

Table 3-6 Survey Respondents' and Study Area Population Household Sizes (N=2,451)

Household Size	Responses	% of Respondents	% Respondents Answering Question	% Population from ACS
1 person	891	36%	36%	42%
2 people	1011	40%	41%	31%
3 people	248	9.9%	10%	13%
4 people	182	7.2%	7.4%	8.8%
5+ people	119	4.7%	4.9%	5.6%

Table 3-7 shows the respondents' residence types. Available population data from the American Community Survey divided households into renter and non-renter, therefore Targeted Marketing data was used for comparison instead. However, even the Targeted Marketing data only divided households into single-family and multi-family. The sample and population are relatively similar in terms of residence types.

Table 3-7 Survey Respondents' Residence Types (N=2,505)

	Residence Type	Responses	% of Respondents	% in Targeted Marketing Database
Single-family	Detached	1593	64%	65%
	Duplex	250	10%	
Multi-family	Apt	618	25%	35%
	Other	44	1.7%	

In addition to the household level demographics, individual demographic questions were asked in the final section of the survey. For these demographics, a similar comparison to the populations from which the respondents belong is included. Table 3-8 displays the gender of the survey respondents. The list of addressees in the study areas apparently have substantially more females than males, according to the Targeted Marketing data, so in this case a comparison to Targeted Marketing data is provided to show the comparison to the genders of the study invitees. Note that the Targeted Marketing database is binary for gender, so those responding with "Prefer not to answer" and "Other" were combined for comparison to the population. Even given the preference to females in the invitation list, the survey respondents appear to be skewed even more heavily toward females.

Table 3-8 Survey Respondents' Genders (N=2,465)

Gender	Responses	% of Respondents	% in Targeted Marketing Database
Female	1454	59%	53%
Male	990	40%	41%
Prefer not to Answer / Other	21	0.8%	

Table 3-9 shows the age ranges of survey respondents alongside those of the population. Visual inspection reveals respondents tended to be older than the population of the combined study areas, which is typical in surveys like this one. The average age of the survey respondents was 50 years old.

Table 3-9 Survey Respondents' Ages (N=2,489)

Age	Responses	% of Respondents	% Population from ACS
18-34	555	22%	40%
35-49	682	27%	25%
50-64	714	28%	22%
65+	538	21%	13%

Table 3-10 shows the race of survey respondents. Most respondents were white, although substantial portions were African-American as well. However, the overrepresentation of whites by 20% is substantial and will be considered for weighting in future models. Note that representation of American Indians / Native Americans and Asians/ Pacific Islanders was small in the ACS data, and these groups were combined with the “Other” category.

Table 3-10 Survey Respondents' Races (N=2,468)

Race	Responses	% of Respondents	% Population from ACS
White / Caucasian	1592	65%	40%
Black / African American	703	29%	55%
Hispanic / Latino	46	1.9%	5.1%
American Indian / Native American	47	1.9%	
Asian / Pacific Islander	54	2.2%	
Other	49	2.0%	5.5%

Individual demographics questions were also asked that have no apparent comparison to the populations to which the respondents belong as this data was not available from the marketing firm where the household addresses were obtained or the American Community Survey (ACS). This section includes these individual-level demographics about the survey respondents.

The employment status of survey respondents is shown in Table 3-11. Many of the respondents either work full time or do not work (either unemployed or retirees). Note that for the remainder of these descriptive statistics in this section there is no readily available population data source for comparison.

Table 3-11 Survey Respondents' Employment Status (N=2,453)

Employment Status	Responses	% of Respondents
Full time	1396	57%
Part time	281	11%
2+ jobs	108	4.4%
Homemaker	95	3.9%
Don't work	663	27%

Finally, a series of questions was asked about respondents' transportation characteristics, including the number of vehicles per household, number of bikes per household, number of licensed drivers per household, and daily and monthly mode usage. In addition to bike ownership and usage, bike confidence was asked as one measure of the possibility that a respondent would bike given different trip characteristics. All of these variables will be explored in greater depth in the future analysis.

Table 3-12 shows the number of vehicles and bicycles owned by survey respondents side by side. Most households owned 1 or 2 vehicles, although a modest portion did not own a vehicle. Many households owned at least one bike; however, more than half did not own a bike.

Table 3-12 Number of Vehicles and Bikes Owned by Survey Respondents (N=2,508; 2,507)

Number of Vehicles	Responses	% of Respondents	Number of Bikes	Responses	% of Respondents
0	257	10%	0	1062	42%
1	914	36%	1	568	23%
2	949	38%	2	486	19%
3	256	10%	3	178	7.1%
4	86	3.4%	4	109	4.3%
5+	46	1.8%	5+	104	4.1%

In terms of bike confidence, the largest percentage (39%) felt very confident in riding a bicycle with only 14% unable to ride and 17% not very confident. Table 3-13 shows bicycling confidence percentages for the survey respondents.

Table 3-13 Respondents' Stated Bike Confidence Level (N=2,422)

Bike Confidence	Responses	% of Respondents
Can't bicycle	260	11%
Not very confident	422	17%
Somewhat confident	619	26%
Very confident	1121	46%

Finally, the reported monthly and daily mode usage (for any purpose) by respondents is shown in Table 3-14. Single-occupant vehicles (SOV) are used regularly by the majority of respondents, with 87% driving alone on at least a monthly basis and 51% on a daily basis. Another 12% are daily carpoolers, although 69% carpool at least once per month. A large portion walk for transportation at least monthly with 56%, and 11% indicated they walk for a daily mode of transportation. Biking is 20% on at least a monthly basis with only 2.1% being daily bicycle transportation users. Thus, there is some confidence that the sample is not substantially skewed toward bicycling enthusiasts.

Table 3-14 Respondents' Monthly and Daily Mode Usage (N=2,513)

Mode	Monthly		Daily	
	Responses	% of Responses	Responses	% of Responses
SOV	2177	87%	1286	51%
Carpool	1723	69%	310	12%
Transit	482	19%	113	4.5%
Taxi	60	2.4%	8	0.3%
Uber	611	24%	9	0.4%
Bike	494	20%	52	2.1%
Walk	1399	56%	286	11%

In summary, over half of respondents reported having at least one bicycle in their household. Additionally, 16% reported biking for utilitarian purposes to some degree, and nearly 31% reported cycling for recreation. The discrepancy between the numbers of casual and regular cyclists provides a sizable portion of the sample that is already accustomed to cycling, but does not bike on a regular basis. Ongoing analysis focuses on this group and the role perceived safety plays in why these individuals choose not to cycle regularly.

3.10 First-wave Statistics Separated by Study Area

The same household demographics were also separated by study area for comparison within each subpopulation. A breakdown of household incomes by study area is presented in Table 3-15. Note that the numbers of individuals who specified "Prefer not to Answer" were removed from this table to provide a more intuitive comparison to the population. As discussed earlier, individuals in higher income brackets were overrepresented in the combined study area. However, it appears that this is mostly the case in the urban areas of Chattanooga/Birmingham and Eastside/Grant Park, and much less prevalent in the smaller communities.

Table 3-15 Household Incomes Separated by Study Area

Household Income	Anniston (N=152)			Opelika (N=146)			Chattanooga (N=196)		
	Sample		Population	Sample		Population	Sample		Population
$15,000 or less	43	28%	30%	26	18%	20%	39	20%	34%
$15,001 - $30,000	32	21%	24%	19	13%	21%	21	11%	23%
$30,001 - $50,000	27	18%	19%	23	16%	18%	27	14%	18%
$50,001 - $75,000	25	16%	16%	24	16%	16%	37	19%	11%
$75,001 - $100,000	7	4.6%	4.0%	23	16%	10%	20	10%	4.9%
$100,001 - $125,000	9	5.9%	2.9%	10	6.8%	6.2%	13	6.6%	4.2%
More than $125,000	9	5.9%	4.3%	21	14%	9.1%	39	20%	5.3%

Household Income	Talladega (N=76)			Northport (N=178)			Birmingham (N=228)		
	Sample		Population	Sample		Population	Sample		Population
$15,000 or less	19	25%	32%	13	7.3%	18%	39	17%	32%
$15,001 - $30,000	14	18%	21%	25	14%	26%	29	13%	22%
$30,001 - $50,000	18	24%	21%	30	17%	19%	26	11%	18%
$50,001 - $75,000	10	13%	15%	43	24%	20%	38	17%	11%
$75,001 - $100,000	7	9.2%	4.1%	32	18%	8.7%	29	13%	7.8%
$100,001 - $125,000	4	5.3%	2.7%	17	9.6%	3.6%	16	7.0%	4.3%
More than $125,000	4	5.3%	4.2%	18	10%	4.6%	51	22%	4.4%

Table 3-15 Household Incomes Separated by Study Area (continued)

Household Income	Eastside (N=393)			Grant Park (N=426)		
	Sample		Population	Sample		Population
$15,000 or less	8	2.0%	15%	13	3.1%	16%
$15,001 - $30,000	15	3.8%	13%	17	4.0%	11%
$30,001 - $50,000	36	9.2%	19%	31	7.3%	12%
$50,001 - $75,000	56	14%	18%	63	15%	16%
$75,001 - $100,000	63	16%	14%	68	16%	13%
$100,001 - $125,000	59	15%	6.4%	64	15%	12%
More than $125,000	156	40%	16%	170	40%	20%

Household Income	Westside (N=199)			South Atlanta (N=163)		
	Sample		Population	Sample		Population
$15,000 or less	42	21%	31%	27	17%	35%
$15,001 - $30,000	36	18%	24%	33	20%	23%
$30,001 - $50,000	32	16%	22%	25	15%	14%
$50,001 - $75,000	31	16%	12%	26	16%	14%
$75,001 - $100,000	32	16%	8.1%	23	14%	5.4%
$100,001 - $125,000	10	5.0%	2.6%	8	4.9%	3.3%
More than $125,000	16	8.0%	1.8%	21	13%	5.1%

Household size by study area is presented in Table 3-16. Each area showed the pattern of overrepresentation of 2-person households, likely implying that couples are more likely to respond than singles or households with additional family members.

Table 3-16 Household Sizes by Study Area

Household Size	Anniston (N=189)			Opelika (N=173)			Chattanooga (N=217)		
	Sample		Population	Sample		Population	Sample		Population
1	71	38%	37%	48	28%	32%	80	37%	42%
2	78	41%	32%	72	42%	36%	96	44%	28%
3	20	11%	13%	23	13%	13%	12	5.5%	13%
4	13	6.9%	10%	15	8.7%	12%	17	7.8%	9.3%
5+	7	3.7%	7.6%	15	8.7%	6.9%	12	5.5%	6.9%

Household Size	Talladega (N=82)			Northport (N=220)			Birmingham (N=249)		
	Sample		Population	Sample		Population	Sample		Population
1	35	43%	33%	71	32%	39%	117	47%	55%
2	32	39%	31%	92	42%	32%	103	41%	25%
3	5	6.1%	16%	21	9.5%	18%	16	6.4%	12%
4	4	4.9%	14%	22	10%	7.8%	6	2.4%	4.5%
5+	6	7.3%	7.3%	14	6.4%	2.7%	7	2.8%	3.2%

Household Size	Eastside (N=420)			Grant Park (N=459)		
	Sample		Population	Sample		Population
1	171	39%	58%	132	28%	39%
2	184	42%	30%	201	42%	36%
3	40	9.2%	7.4%	50	10%	13%
4	22	5.1%	4.7%	60	13%	9.0%
5+	3	0.7%	0.7%	16	3.4%	3.5%

Household Size	Westside (N=221)			South Atlanta (N=180)		
	Sample		Population	Sample		Population
1	72	31%	38%	83	44%	39%
2	85	36%	29%	50	26%	27%
3	31	13%	14%	27	14%	16%
4	14	6.0%	8.0%	8	4.2%	8.5%
5+	19	8.1%	11%	12	6.3%	9.2%

Table 3-17 shows the breakdown of residence types by study area compared to the targeted marketing data (for single- vs multi-family housing). Several sites had a slight overrepresentation from detached residences, but few major discrepancies arise.

Table 3-17 Residence Types by Study Area

Residence Type	Anniston (N=195)			Opelika (N=177)			Chattanooga (N=226)		
	Sample		TM* Data	Sample		TM* Data	Sample		TM* Data
Detached	157	81%	86%	143	81%	71%	116	51%	60%
Duplex	14	7.2%		9	5.1%		20	8.8%	
Apt	18	9.2%	14%	18	10%	29%	88	39%	40%
Other	6	3.1%		7	4.0%		2	0.9%	

Residence Type	Talladega (N=88)			Northport (N=220)			Birmingham (N=249)		
	Sample		TM* Data	Sample		TM* Data	Sample		TM* Data
Detached	76	86%	85%	163	72%	68%	104	40%	49%
Duplex	4	4.5%		17	7.6%		20	7.6%	
Apt	8	9.1%	15%	44	20%	32%	134	51%	51%
Other	0	0.0%		1	0.4%		5	1.9%	

Residence Type	Eastside (N=432)			Grant Park (N=477)		
	Sample		TM* Data	Sample		TM* Data
Detached	179	41%	39%	352	74%	65%
Duplex	67	15%		74	16%	
Apt	183	42%	61%	48	10%	35%
Other	3	0.7%		3	0.6%	

Residence Type	Westside (N=233)			South Atlanta (N=189)		
	Sample		TM* Data	Sample		TM* Data
Detached	183	78%	74%	125	66%	63%
Duplex	16	6.8%		9	4.7%	
Apt	31	13%	26%	49	26%	37%
Other	3	1.3%		6	3.2%	

*TM=Targeted Marketing

Responses for gender are compared to the population (from the targeted marketing data) for each area in Table 3-18. There were more females than males in each area according to the targeted marketing data, however, responses from each area were even more female-heavy. This likely implies that the deviance from the population is distributed among study areas and is only statistically perceivable for the combined population.

Table 3-18 Gender by Study Area

Gender	Anniston (N=190)			Opelika (N=177)			Chattanooga (N=220)		
	Sample		TM* Data	Sample		TM* Data	Sample		TM* Data
Female	114	60%	57%	112	63%	57%	131	60%	53%
Male	75	39%	39%	65	37%	38%	87	40%	42%

Gender	Talladega (N=82)			Northport (N=221)			Birmingham (N=259)		
	Sample		TM* Data	Sample		TM* Data	Sample		TM* Data
Female	55	67%	55%	143	65%	59%	143	55%	49%
Male	27	33%	40%	77	35%	36%	112	43%	45%

Gender	Eastside (N=424)			Grant Park (N=470)		
	Sample		TM* Data	Sample		TM* Data
Female	237	55%	53%	263	55%	53%
Male	187	43%	47%	207	43%	47%

Gender	Westside (N=222)			South Atlanta (N=187)		
	Sample		TM* Data	Sample		TM* Data
Female	153	65%	56%	103	54%	55%
Male	69	29%	44%	84	44%	45%

*TM=Targeted Marketing

Age distributions compared to populations of each area compared to ACS population data are presented in Table 3-19. Across all study areas there was a greater response rate among senior citizens (over 65), though the more rural areas had a greater share of senior citizens responding than the other areas.

Table 3-19 Age Distribution by Study Area

Age	Anniston (N=184)			Opelika(N=171)			Chattanooga (N=212)		
	Responses		Population	Responses		Population	Responses		Population
18-34	15	8.2%	29%	23	13%	30%	40	19%	46%
35-49	29	16%	21%	41	24%	22%	49	23%	21%
50-64	64	35%	30%	62	36%	28%	79	37%	21%
65+	76	41%	20%	45	26%	20%	44	21%	12%

Age	Talladega (N=80)			Northport (N=215)			Birmingham (N=251)		
	Responses		Population	Responses		Population	Responses		Population
18-34	8	10%	32%	46	21%	40%	72	29%	52%
35-49	10	13%	25%	40	19%	18%	45	18%	19%
50-64	27	34%	26%	69	32%	21%	77	31%	17%
65+	35	44%	17%	60	28%	20%	57	23%	11%

Age	Eastside (N=428)			Grant Park (N=471)		
	Responses		Population	Responses		Population
18-34	149	34%	49%	120	25%	42%
35-49	166	38%	28%	191	40%	33%
50-64	78	18%	16%	112	23%	18%
65+	35	8.1%	6.7%	48	10%	6.9%

Age	Westside (N=222)			South Atlanta (N=186)		
	Responses		Population	Responses		Population
18-34	45	19%	30%	33	17%	39%
35-49	51	22%	29%	55	29%	30%
50-64	72	31%	26%	59	31%	22%
65+	54	23%	16%	39	21%	9.2%

The racial breakdown of respondents by area is presented in Table 3-20. There was a heavy overrepresentation of white respondents in each area. White / Caucasian was the most common reported race in almost all areas, even though it is not the most common in most areas according to population data from ACS. Note that since respondents can identify as multiple races, percentages may exceed 100.

Table 3-20 Race Distribution by Study Area

Race	Anniston (N=189)			Opelika (N=175)			Chattanooga (N=220)		
	Sample		Population	Sample		Population	Sample		Population
White / Caucasian	96	51%	36%	123	70%	45%	144	65%	43%
Black / African American	80	42%	61%	47	27%	51%	64	29%	52%
Hispanic / Latino	1	0.5%		0	0.0%		3	1.4%	
Asian / Pacific Islander	1	0.5%		2	1.1%		1	0.5%	
American Indian / Native American	5	2.6%		6	3.4%		6	2.7%	
Other	3	1.6%	5.0%	2	1.1%	7.9%	6	2.7%	11%

Race	Talladega (N=84)			Northport (N=218)			Birmingham (N=259)		
	Sample		Population	Sample		Population	Sample		Population
White / Caucasian	54	64%	40%	182	83%	56%	172	66%	41%
Black / African American	27	32%	57%	24	11%	39%	70	27%	53%
Hispanic / Latino	0	0.0%		3	1.4%		2	0.8%	
Asian / Pacific Islander	0	0.0%		1	0.5%		11	4.2%	
American Indian / Native American	3	3.6%		4	1.8%		8	3.1%	
Other	1	1.2%	11%	3	1.4%	9.3%	4	1.5%	11%

Table 3-20 Race Distribution by Study Area (continued)

Race	Eastside (N=428) Sample		Eastside (N=428) Population	Grant Park (N=473) Sample		Grant Park (N=473) Population
White / Caucasian	339	79%	55%	371	78%	58%
Black / African American	49	11%	37%	63	13%	36%
Hispanic / Latino	10	2.3%	3.9%	18	3.8%	5.7%
Asian / Pacific Islander	23	5.4%		8	1.7%	
American Indian / Native American	1	0.2%		4	0.9%	
Other	9	2.1%	8.6%	8	1.7%	6.3%

Race	Westside (N=227) Sample		Westside (N=227) Population	South Atlanta (N=188) Sample		South Atlanta (N=188) Population
White / Caucasian	53	23%	4.7%	59	31%	19%
Black / African American	163	72%	93%	116	62%	71%
Hispanic / Latino	6	2.6%	1.7%	3	1.6%	11%
Asian / Pacific Islander	3	1.3%		5	2.7%	
American Indian / Native American	7	3.1%		3	1.6%	
Other	5	2.2%	2.7%	7	3.7%	9.8%

The employment status breakdown for each area is presented in Table 3-21. Anniston and Talladega had larger portions of individuals who don’t work, consistent with the earlier findings of higher portions of individuals in retirement age (over 65).

Table 3-21 Employment Status by Study Area

Employment Status	Anniston (N=188)		Opelika (N=173)		Chattanooga (N=220)	
Full time	44	23%	69	40%	108	49%
Part time	23	12%	28	16%	34	15%
2+ jobs	5	2.7%	8	4.6%	5	2.3%
Homemaker	14	7.4%	8	4.6%	13	5.9%
Don't work	107	57%	66	38%	66	30%

Employment Status	Talladega (N=83)		Northport (N=222)		Birmingham (N=258)	
Full time	22	27%	106	48%	144	56%
Part time	9	11%	35	16%	19	7%
2+ jobs	2	2.4%	6	2.7%	10	3.9%
Homemaker	4	4.8%	11	5.0%	5	1.9%
Don't work	47	57%	71	32%	88	34%

Employment Status	Eastside (N=427)		Grant Park (N=473)	
Full time	346	81%	355	75%
Part time	32	7.5%	44	9.3%
2+ jobs	18	4.2%	19	4.0%
Homemaker	10	2.3%	14	3.0%
Don't work	35	8.2%	59	12%

Employment Status	Westside (N=223)		South Atlanta (N=186)	
Full time	102	46%	100	54%
Part time	30	13%	27	15%
2+ jobs	23	10%	12	6.5%
Homemaker	11	4.9%	5	2.6%
Don't work	71	32%	53	29%

Vehicle ownership data for each area is presented in Table 3-22. Opelika and Northport had greater portions of respondents with at least one vehicle.

Table 3-22 Number of Vehicles Owned by Study Area

Vehicles per Household	Anniston (N=190)		Opelika (N=175)		Chattanooga (N=220)	
0	24	13%	12	7%	32	15%
1	71	37%	46	26%	69	31%
2	60	32%	74	42%	81	37%
3	20	11%	25	14%	23	10%
4	10	5.3%	12	6.9%	8	3.6%
5+	5	2.6%	6	3.4%	7	3.2%

Vehicles per Household	Talladega (N=87)		Northport (N=222)		Birmingham (N=265)	
0	11	13%	10	4.5%	35	13%
1	30	34%	78	35%	105	40%
2	25	29%	81	36%	92	35%
3	15	17%	37	17%	21	7.9%
4	0	0.0%	14	6.3%	8	3.0%
5+	6	6.9%	2	0.9%	4	1.5%

Vehicles per Household	Eastside (N=428)		Grant Park (N=471)		Westside (N=223)		South Atlanta (N=183)	
0	21	4.8%	26	5.5%	41	17%	37	19%
1	194	45%	149	31%	92	39%	65	34%
2	170	39%	229	48%	63	27%	62	33%
3	28	6.5%	49	10%	18	7.7%	15	7.9%
4	12	2.8%	11	2.3%	6	2.6%	3	1.6%
5+	3	0.7%	7	1.5%	3	1.3%	1	0.5%

Bicycle ownership for each area is represented in Table 3-23. Chattanooga had fewer households without access to a bike, even compared to its control area of Birmingham.

Table 3-23 Number of Bikes Owned by Study Area

Bikes per Household	Anniston (N=191)		Opelika (N=173)		Chattanooga (N=219)	
0	114	60%	93	54%	95	43%
1	36	19%	34	20%	43	20%
2	24	13%	21	12%	41	19%
3	12	6.3%	11	6.4%	17	7.8%
4	3	1.6%	6	3.5%	12	5.5%
5+	2	1.0%	8	4.6%	11	5.0%

Bikes per Household	Talladega (N=88)		Northport (N=223)		Birmingham (N=265)	
0	58	66%	118	53%	140	53%
1	12	14%	46	21%	69	26%
2	10	11%	31	14%	36	14%
3	4	4.5%	12	5.4%	13	4.9%
4	2	2.3%	9	4.0%	1	0.4%
5+	2	2.3%	7	3.1%	6	2.3%

Bikes per Household	Eastside (N=428)		Grant Park (N=472)		Westside (N=220)		South Atlanta (N=183)	
0	105	24%	112	23%	99	42%	99	52%
1	129	30%	95	20%	59	25%	38	20%
2	113	26%	140	29%	38	16%	25	13%
3	36	8.3%	48	10%	10	4.3%	13	6.8%
4	26	6.0%	35	7.3%	11	4.7%	4	2.1%
5+	19	4.4%	42	8.8%	3	1.3%	4	2.1%

Respondents' stated bike confidence levels are tabulated in Table 3-24. The smaller areas (Anniston and Talladega) had larger portions of those who can't bike, while the small urban areas (Chattanooga and Birmingham) had larger portions of those reporting as "very confident", and the most urban areas (Eastside and Grant Park) had the highest levels of reported confidence. There is somewhat of a small discrepancy between many treatment areas and their respective control areas, as some treatment areas have a larger portion of respondents who cannot bike.

Table 3-24 Respondents' Stated Bike Confidence Level by Study Area

Bike Confidence	Anniston (N=182)		Opelika (N=171)		Chattanooga (N=215)	
Can't Bike	48	26%	26	15%	30	14%
Not Very Confident	29	16%	34	20%	36	17%
Somewhat Confident	36	20%	47	27%	49	23%
Very Confident	69	38%	64	37%	100	47%

Bike Confidence	Talladega (N=79)		Northport (N=212)		Birmingham (N=254)	
Can't Bike	17	22%	21	10%	21	8.3%
Not Very Confident	21	27%	41	19%	42	17%
Somewhat Confident	15	19%	67	32%	68	27%
Very Confident	26	33%	83	39%	123	48%

Bike Confidence	Eastside (N=430)		Grant Park (N=473)		Westside (N=222)		Southside (N=184)	
Can't Bike	13	3.0%	21	4.4%	38	16%	25	13%
Not Very Confident	66	15%	69	14%	44	19%	40	21%
Somewhat Confident	119	27%	137	29%	43	18%	38	20%
Very Confident	232	54%	246	52%	97	41%	81	43%

3.11 First-wave Statistics Segmented by Rider Status

The same household characteristics were also computed based on segments of different rider status among the combined study group. The four rider statuses are potential rider, recreational, utilitarian, and those that cannot bike. The criteria for inclusion in one of these categories comes from the responses to questions regarding bicycling confidence, cycling distances for recreation/utilitarian purpose, and cycling trip frequency for commute/other purposes. The 4 segments and their criteria are:

1. Potential cyclist (N=1348)—those who report zero miles of cycling per month, but report being able to ride a bike, regardless of confidence level.
2. Recreational cyclist (N=496)—those who bike a non-zero distance per month, but bike less than once a month *and* less than a mile a week, on average, for utilitarian purposes.
3. Utilitarian cyclist (N=318)—those who bike at least once a month *or* at least a mile a week, on average, for utilitarian purposes.
4. Cannot bike (N=260)—those who state that they cannot ride a bicycle.

The statistics presented do not have a comparison to the population, as there is no readily available population-level data for rider type segmentation. Note that those who did not answer the bike confidence question were not able to be included in the segmentation. The distribution of each rider type in each site is presented in Table 3-25.

Table 3-25 Rider Status Class Makeup for each Neighborhood

Rider Status	Potential		Recreational		Utilitarian		Cannot Bike	
Anniston	108	9.1%	21	4.2%	5	3.8%	48	12%
Opelika	113	9.5%	20	8.0%	12	9.3%	26	14%
Chattanooga	118	4.4%	38	1.3%	29	0.3%	30	8.0%
Talladega	55	12%	6	7.2%	1	2.6%	17	9.9%
Northport	149	13%	34	9.9%	8	9.3%	21	9.9%
Birmingham	157	15%	47	25%	29	36%	21	6.1%
Eastside	183	18%	120	29%	113	29%	13	9.9%
Grant Park	222	11%	140	6.9%	91	5.8%	21	18%
Westside	133	8.9%	33	7.8%	18	3.8%	38	12%
South Atlanta	110	9.1%	37	4.2%	12	3.8%	25	12%

Income for each of these segments is presented in Table 3-26. Household income for both current cyclist groups tended to be much higher, while those that cannot bike were overrepresented in the lower income categories.

Table 3-26 Household Income Distribution by Rider Status

Household Income	Potential (N=1153)		Recreational (N=444)		Utilitarian (N=297)		Cannot Bike (N=200)	
$15,000 or less	124	11%	24	5.4%	17	5.7%	78	39%
$15,001 - $30,000	148	13%	18	4.1%	14	4.7%	51	26%
$30,001 - $50,000	164	14%	45	10%	33	11%	21	11%
$50,001 - $75,000	215	19%	67	15%	45	15%	22	11%
$75,001 - $100,000	168	15%	70	16%	42	14%	16	8.0%
$100,001 - $125,000	105	9.1%	60	14%	42	14%	4	2.0%
More than $125,000	229	20%	160	36%	104	35%	8	4.0%

Distributions for household sizes by rider type are presented in Table 3-27. Single-person households were overrepresented in the group of individuals who cannot bike. Large households were overrepresented among both recreational and utilitarian cyclist groups.

Table 3-27 Household Size Distribution by Rider Status

Household Size	Potential (N=1306)		Recreational (N=481)		Utilitarian (N=308)		Cannot Bike (N=241)	
1	479	37%	144	30%	98	32%	122	51%
2	541	41%	204	42%	135	44%	88	37%
3	138	11%	65	14%	23	7.5%	14	5.8%
4	88	6.7%	41	8.5%	39	13%	9	3.7%
5+	60	4.6%	27	5.6%	13	4.2%	7	2.9%

Residence types for each rider type are presented in Table 3-28. Utilitarian cyclists were less likely to live in a detached residence, indicating that there may be a linkage between utilitarian cycling and urban environment.

Table 3-28 Residence Type Distribution by Rider Status

Residence Type	Potential (N=1344)		Recreational (N=496)		Utilitarian (N=318)		Cannot Bike (N=259)	
Detached	878	65%	328	66%	177	56%	158	61%
Apt	123	9.2%	49	9.9%	46	14%	18	6.9%
Duplex	329	24%	109	22%	92	29%	69	27%
Other	14	1.1%	8	1.6%	3	0.9%	14	5.4%

Responses for gender are reported by rider type in Table 3-29. Females were overrepresented in both non-rider groups. Recreational cyclists were closer to an even split (despite the pooled sample being predominantly female), and a majority of utilitarian cyclists were male.

Table 3-29 Gender Distribution by Rider Status

Gender	Potential (N=1336)		Recreational (N=494)		Utilitarian (N=318)		Cannot Bike (N=257)	
Male	496	37%	222	45%	192	60%	62	24%
Female	828	62%	267	54%	122	38%	195	76%
Other / Prefer not to specify	12	1.0%	5	1.0%	4	1.3%	0	0.0%

Respondents' ages for each rider type are presented in Table 3-30. Not surprisingly, a large part of those who cannot bike are those 65 years old or older. Utilitarian cyclists are likewise more likely to be under 35. Little variation is noted between the age distributions for potential and recreational cyclists.

Table 3-30 Age Distribution by Rider Status

Age	Potential (N=1346)		Recreational (N=495)		Utilitarian (N=318)		Cannot Bike (N=260)	
<35	289	21%	128	26%	125	39%	9	3.5%
35-49	339	25%	192	39%	117	37%	28	11%
50-64	405	30%	122	25%	66	21%	95	37%
65+	312	23%	53	11%	10	3.1%	128	49%

Respondents' race by rider type is presented in Table 3-31. African-Americans appeared to be overrepresented in the group of those who cannot bike, while utilitarian cyclists appeared to be overrepresented by Caucasians.

Table 3-31 Race Distribution by Rider Status

Race	Potential (N=1339)		Recreational (N=492)		Utilitarian (N=318)		Cannot Bike (N=259)	
American Indian / Native American	22	1.6%	7	1.4 %	8	2.5%	8	3.1%
Asian / Pacific Islander	26	1.9%	13	2.6%	12	3.8%	2	0.8%
Black / African American	398	30%	98	20%	33	10%	141	54%
White / Caucasian	856	64%	365	74%	247	78%	103	40%
Hispanic / Latino	22	1.6%	10	2.0%	10	3.1%	1	0.4%
Other	28	2.1%	5	1.0%	11	3.5%	4	1.5%

Table 3-32 shows the employment status breakdown for each rider type group. As expected with the overrepresentation of senior adults in the cannot bike category, a majority of those in that category do not work. Utilitarian cyclists were also much more likely to work full-time.

Table 3-32 Employment Status Distribution by Rider Status

Employment Status	Potential (N=1332)		Recreational (N=492)		Utilitarian (N=317)		Cannot Bike (N=255)	
Full time	743	56%	353	72%	247	78%	45	18%
Part time	171	13%	47	10%	33	10%	22	8.6%
2+ jobs	48	3.6%	27	5.5%	25	7.9%	4	1.6%
Homemaker	43	3.2%	26	5.3%	8	2.5%	17	6.7%
Don't work	361	27%	68	14%	24	7.6%	170	67%

Vehicle and bike ownership broken down by rider types are presented in Table 3-33. Zero-vehicle households were overrepresented in the group of those who cannot bike, pointing to a double transportation disadvantage for those households. Households with three or more vehicles were overrepresented in the potential and recreational rider groups, indicating that both utilitarian cyclists and those who cannot bike are less likely to own many vehicles. Interestingly, five utilitarian cyclists report not owning a bike. Four of the five reported elsewhere in the survey that they are current users of bikeshare, while the fifth reported using bikeshare in the past.

Table 3-33 Number of Vehicles and Bikes Owned by Rider Status

Vehicles per Household	Potential (N=1329)		Recreational (N=490)		Utilitarian (N=314)		Cannot Bike (N=252)	
0	115	8.7%	20	4.1%	22	7.0%	70	28%
1	486	37%	153	31%	121	39%	106	42%
2	516	39%	228	47%	121	39%	56	22%
3	137	10%	60	12%	34	11%	14	5.6%
4	46	3.5%	20	4.1%	11	3.5%	5	2.0%
5+	28	2.1%	8	1.6%	5	1.6%	1	0.4%

Bikes per Household	Potential (N=1328)		Recreational (N=490)		Utilitarian (N=313)		Cannot Bike (N=251)	
0	717	54%	37	7.6%	8	2.6%	210	84%
1	298	22%	143	29%	87	28%	24	9.6%
2	200	15%	181	37%	85	27%	9	3.6%
3	57	4.3%	62	13%	51	16%	4	1.6%
4	39	2.9%	33	6.7%	31	9.9%	3	1.2%
5+	16	1.2%	34	6.9%	46	15%	1	0.4%

Table 3-34 shows respondents' stated level of bike confidence, segmented by rider type. By definition, all those who state they cannot bike are in the category of "cannot bike." Respondents of all confidence levels were present in the potential rider group. There are higher representations of more confident riders in both the recreational and utilitarian groups.

Table 3-34 Respondent's Stated Level of Bike Confidence by Rider Status

Confidence Level	Potential (N=1348)		Recreational (N=496)		Utilitarian (N=318)		Cannot Bike (N=260)	
Can't Bike	0	0%	0	0%	0	0%	260	100%
Not Very Confident	395	29%	26	5.2%	1	0.3%	0	0%
Somewhat Confident	445	33%	134	27%	40	13%	0	0%
Very Confident	508	38%	336	68%	277	87%	0	0%

CHAPTER 4. PREFERENCES FOR BICYCLE INFRASTRUCTURE IN COMMUNITIES WITH EMERGING CYCLING CULTURES

This chapter contains discussion on the initial analysis that took place data from the first six sites (Chattanooga, TN, and Anniston, Opelika, Birmingham, Talladega, and Northport, AL). The analyses and discussion in this chapter have been published in Transportation Research Record (Clark et al. 2019). From the sample of 23,413 recipients in these communities there were 1,178 usable responses, 176 of which were online responses, after removing severely incomplete cases. The sociodemographics for the pooled sample, compared with the 2014 ACS estimates for the same combined area, are presented in Table 4-1.

As is typical for self-administered surveys of the general population, there are sizable differences between the sample and the population on a number of variables. The small chi-squared goodness of fit test values for the presented demographics indicates a deviance of the sample from the population. The respondents tend to be wealthier than the study area populations. Inspection of the data indicates that one-person households were underrepresented in the sample, while two-person households were overrepresented. Respondents also tended to be older than the population of the combined study areas, which is common in surveys like this one, as older individuals are likely to have more time to respond to surveys. The average age of the survey respondents was 52 years old.

The non-representativeness of the sample is somewhat limiting in terms of how accurately the data can *describe* the overall population. However, when applied in an *explanatory* sense, as with the regression models in this study, the "potential defect" presented by such a sample "is less significant than it would be in descriptive research" (Babbie 2010). The existence of a non-response bias limits our ability to describe the preferences of the population as a whole, but not necessarily to explain the relationships between variables. Including sociodemographics in models is a time-honored way of controlling for non-response bias.

Table 4-1 Sociodemographics for Pooled Sample and American Community Survey (ACS) Population

	Responses	% Respondents Answering Question*	% Population from ACS
Household Income (N=1,146; Chi-squared goodness of fit P<0.001)			
$15,000 or less	179	18%	29%
$15,001 - $30,000	140	14%	23%
$30,001 - $50,000	151	15%	19%
$50,001 - $75,000	177	18%	14%
$75,001 - $100,000	118	12%	6.4%
$100,001 - $125,000	69	7.1%	4.2%
More than $125,000	142	15%	5.6%
Household Size (N=1,130; Chi-squared goodness of fit P<0.001)			
1 person	422	37%	40%
2 people	473	42%	31%
3 people	97	8.6%	14%
4 people	77	6.8%	9.7%
5+ people	61	5.4%	6.1%
Respondent Age (N=1,113; Chi-squared goodness of fit P<0.001)			
18-34	204	18%	40%
35-49	214	19%	21%
50-64	378	34%	23%
65+	317	28%	16%
*Respondent Race/Ethnicity** (N=1,145; Chi-squared goodness of fit P<0.001)*			
Black / African American	312	27%	52%
White / Caucasian	771	67%	43%
Hispanic / Latino	9	0.8%	4.6%
Other	67	5.9%	4.6%

*Excluding those who specified "Prefer not to answer"

**Respondents were allowed to mark more than one (percentages may exceed 100%)

Vehicle and bicycle ownership are presented in Table 4-2. Most households owned 1 or 2 vehicles, although a modest portion did not own a vehicle. More than half of the households did not own a bike. Nevertheless (table not presented), about 11% of respondents reported biking for utilitarian purposes on at least a monthly basis. Additionally, nearly 20% reported cycling for recreation to some degree. However, only 1% of respondents reported daily utilitarian cycling. This discrepancy, between the number of daily utilitarian cyclists with both the number of respondents who cycle infrequently and the number who have access to a bike in their household, indicates there is a sizable portion of the sample that is able to ride a bike but does not bike on a regular basis.

Table 4-2 Number of Vehicles and Bikes Owned by Survey Respondents (N=1,159)

Number of Vehicles	Responses	% of Respondents	Number of Bikes	Responses	% of Respondents
0	124	11%	0	618	53%
1	399	34%	1	240	21%
2	413	36%	2	163	14%
3	141	12%	3	69	6.0%
4	52	4.5%	4	33	2.8%
5	16	1.4%	5	13	1.1%
6	8	0.7%	6	15	1.3%
7+	6	0.5%	7+	8	0.7%

4.1 User Preferences

Survey respondents were presented with different configurations of roadway characteristics and infrastructure types, and asked to state their perceived level of comfort, safety, and willingness to try the presented infrastructure. Responses were converted to numeric values, with *Strongly disagree* equal to 1 and *Strongly agree* equal to 5. The average ratings for comfort, safety, and willingness to try are presented in Figure 4-1, Figure 4-2, and Figure 4-3, respectively. As mentioned previously, each version of the survey focused on the continuum of four infrastructure types within the same traffic lane and parking lane combination, plus two additional images duplicated from the other survey versions. To avoid the potential framing effects introduced by the insertion of these additional images “out of sequence”, only the responses for the in-sequence images are included in the descriptive analysis presented here (sample size between 266 and 308 for each mean); all responses are included in the regression analysis reported below.

The characteristics of the bicycle infrastructure portion of the roadways for the sharrow, bike lane, and buffered bike lane cases were consistent between roadway configurations. However, protected bike lanes had two variations, one-way and two-way, only one of which was presented for a given configuration in order to limit the number of images presented. The broken lines on the graphs show the point in the progression of bicycle infrastructure where barrier-protection is introduced, with the two different protected bicycle infrastructure types being presented under a single label. The two-lane/no parking and four-lane with parking configurations had one-way protected bike lanes (indicated by the dotted line), while the four-lane/no parking and two-lane with parking ones had two-way protected bike lanes (indicated by the dash-dot lines). Given the relative lack of variation in the protected bike lane ratings, these figures indicate that the differences in ratings between protected bike lane scenarios may be unrelated to roadway characteristics.

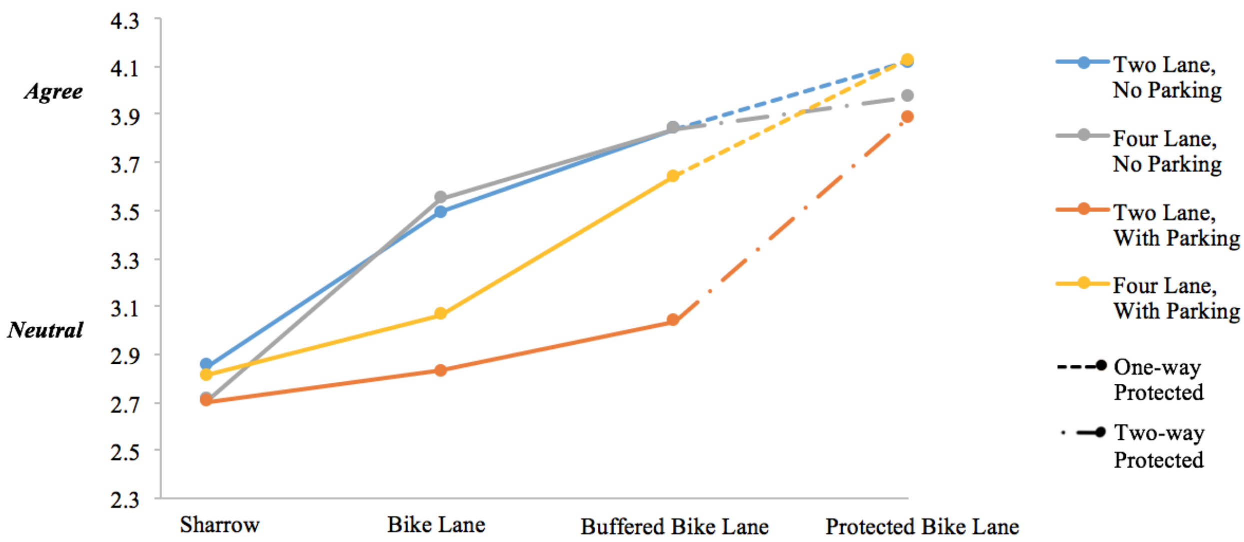


Figure 4-1 Average expressed *comfort* levels for each lane/parking configuration by bicycle infrastructure type.

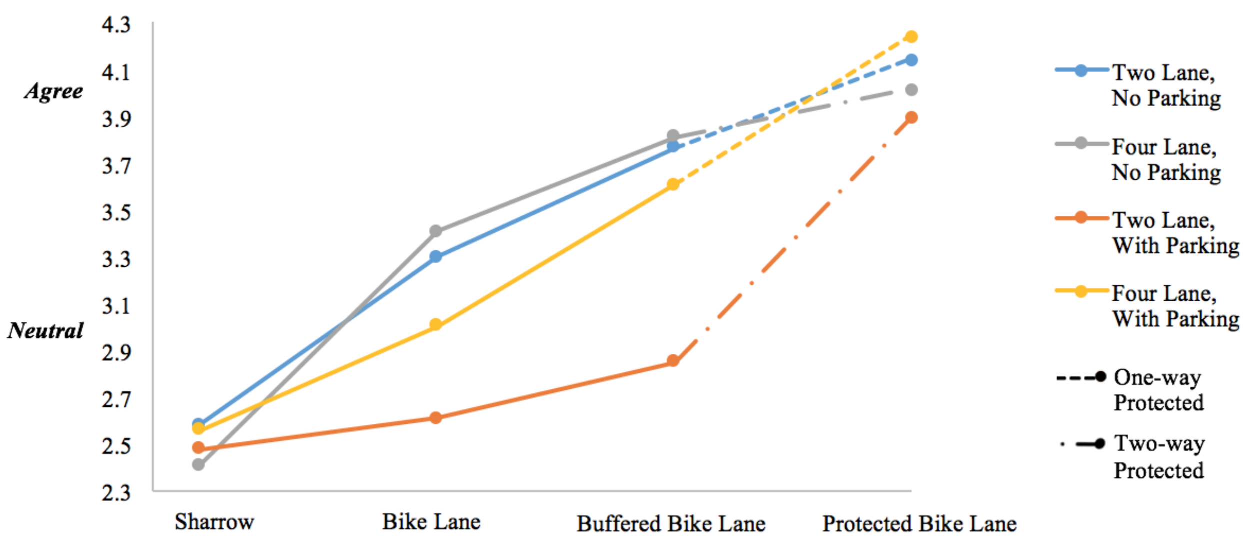


Figure 4-2 Average expressed *safety* levels for each lane configuration by bicycle infrastructure type.

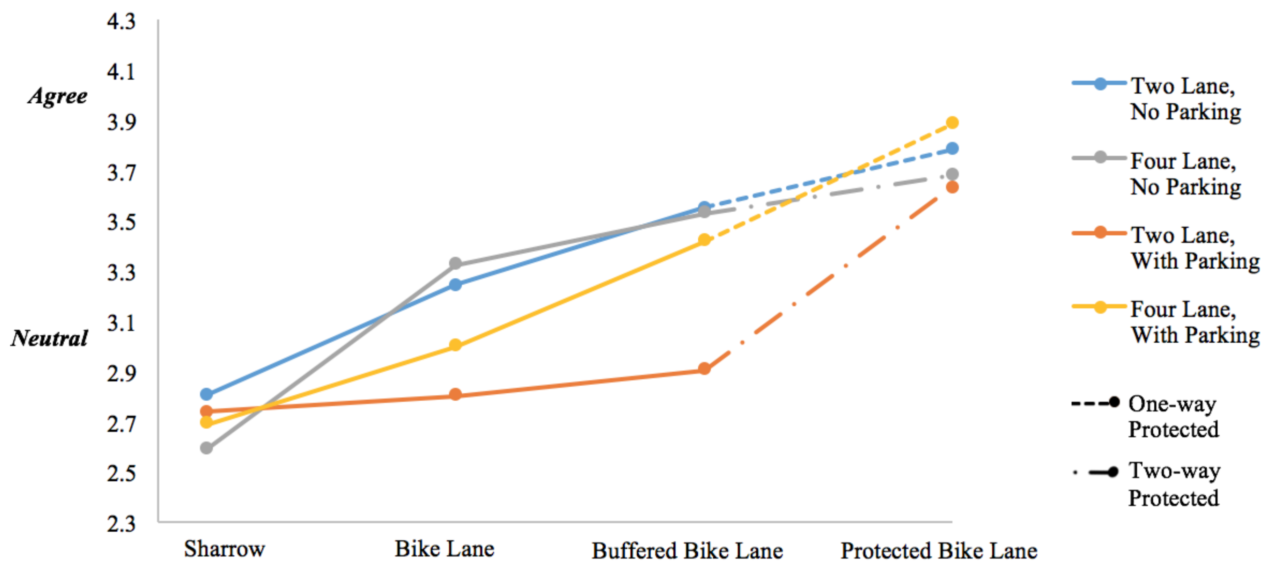


Figure 4-3 Average expressed level of *willingness to try* for each lane configuration by bicycle infrastructure type.

Ratings for the three different measures tended to follow the same patterns. This indicates that respondents did not make much distinction between the different questions for each image, which may result from a lack of experience that would allow one to rate a given infrastructure as safe but not comfortable, or vice versa, for example.

Each of the three measures improved for each increased degree of separation provided by the bicycling infrastructure, indicating a positive benefit associated with separation from moving and parked cars. Each version of the survey began the infrastructure image section with a sharrow configuration, which allows the sharrow infrastructure layouts to serve as a base measurement for each lane configuration. In each version, the sharrow configurations received the lowest ratings, and the existence of any sort of spatial separation was influential in increasing each perception measure. Average ratings for each traditional bike lane scenario were higher than those for sharrows on the same roadway configuration. The difference is more pronounced for bicycle lanes without adjacent curb parking. Buffered bike lanes received higher average ratings than traditional bike lanes, and also saw the same disutility of parking lanes.

4.2 Infrastructure and Roadway Traits

While the descriptive analysis of the preceding subsection is useful, it is also desirable to control for a number of covariates whose effects might otherwise be confounded with those of infrastructure type and roadway configuration. Linear regression models were built using the multiple responses by 1,178 respondents for each of the three dependent variables (comfort, safety, and willingness to try). Dummy variables for each infrastructure type, along with the presence of on-street parking and additional lanes of traffic, were included in the models. Although treating Likert-type data as continuous variables technically violates some assumptions associated with linear regression models, such models are commonly viewed as being robust with respect to violations of the "required" assumptions, and ordinal data can serve as a reliable approximation to a continuous scale with "little worry" when there are four or more response levels, as is the case here (Bentler and Chou 1987). Much empirical research over the years has used Likert-type data with parametric methods such as regression, and a review of the progression of this research assures scholars that such methods can be employed in these cases "with no fear of 'coming to the wrong conclusion' " (Norman 2010).

An issue resulting from the survey design was the emergence of a framing effect. Each version of the survey had a logical sequence of four images based on a common lane configuration, along with two out-of-sequence images. Each out-of-sequence image, which was a repeat of an image displayed in another version of the survey, appeared either before or after the most conceptually similar image of the sequence. Five roadway images appeared in more than one version (bike lane with two auto lanes and no parking, buffered bike lane with two auto lanes and no parking, buffered bike lane with four auto lanes and no parking, bike lane with two auto lanes and parking, and bike lane with four auto lanes and parking). Each of these images received different responses based on the version in which they appeared. Specifically, these images attracted different responses when they were out-of-sequence (e.g. the "two-lane/no parking bike lane" image in Version 1 of Figure 3-5) than when they were in-sequence (the same image in Version 2). The multi-use path appeared in three versions and had consistent scores in each version.

Dummy variables were included in the regression to capture the variation due to the framing effects introduced by the interruption of the natural sequence of each version. Most images, when compared to the preceding image, changed only one variable (bike facility type, parking, or auto lanes). Conversely, each time the sequence is broken, two variables must be changed at once, either to break the sequence or to return to the sequence. For example, the bike lane with two auto lanes and parking in version 3 (in Figure 3-6) breaks the sequence, changing the number of auto lanes (from four to two) and the bike facility type (from sharrow to bike lane) from the previous image; however, the (out-of-sequence) bike lane with four auto lanes and parking in version 4 only changes one variable from the preceding image (the addition of parking), while the subsequent image changes two variables at once, the change of bike lane to buffered bike lane and the removal of parking. Three dummy variables were created and applied to the appropriate images when their appearance involved changing two variables at once: Bike Lane (BL)-No Parking, Buffered Bike Lane (BBL)-No Parking, and BL-Two Lanes. The BL-No Parking variable was set to 1 for the second image in version 1, which added a bike lane and removed parking compared to the preceding image; the BBL-No Parking variable was set to 1 for the two-lane buffered bike lane image in Version 1 along with the four-lane buffered bike lane in Version 4, both of which added a buffer to the bike lane and removed parking compared to the preceding image; and the BL-Two Lanes variable was set to 1 for the second image in Version 3, which introduced a bike lane and removed the additional lanes of traffic compared to the preceding image. A fourth dummy variable was also considered for the two-lane one-way protected bike lane without parking image in Version 2, however this variable was eventually excluded because it undermined the stability of the model, perhaps due to empirical collinearity issues related to the infrequent appearance of one-way protected bike lanes. The results of the linear regression for each dependent variable are presented in Table 4-3.

Table 4-3 Linear Regression for Expressed Comfort, Safety, and Willingness to Try by Infrastructure Characteristics

Variable	Comfort			Safety			Willingness to Try		
			P			P			P
Constant	2.90	***	<0.001	2.62	***	<0.001	2.82	***	<0.001
Bicycle Infrastructure Types									
Bike Lane (BL)	0.37	***	<0.001	0.45	***	<0.001	0.30	***	<0.001
Buffered BL (BBL)	0.73	***	<0.001	0.89	***	<0.001	0.57	***	<0.001
One-way Protected	1.34	***	<0.001	1.68	***	<0.001	1.12	***	<0.001
Two-way Protected	1.16	***	<0.001	1.45	***	<0.001	0.96	***	<0.001
Multi-use	1.24	***	<0.001	1.53	***	<0.001	1.12	***	<0.001
Roadway Characteristics									
Parking	-0.27	***	<0.001	-0.26	***	<0.001	-0.17	***	<0.001
Four Lanes	0.02		0.477	0.05		0.103	-0.02		0.500
Framing Effects									
BL-No Parking	0.42	***	<0.001	0.50	***	<0.001	0.41	***	<0.001
BBL-No Parking	0.22	***	<0.001	0.33	***	<0.001	0.22	**	0.002
BL-Two Lanes	0.28	***	<0.001	0.35	***	<0.001	0.22	*	0.015
# of Responses	6743			6723			6664		
R^2	0.175			0.232			0.093		
Adj R^2	0.174			0.231			0.092		

*Significant at P = 0.050 or better

**Significant at P = 0.010 or better

***Significant at P < 0.001

The dummy variables for each infrastructure type were significant, with each degree of separation including a larger coefficient, supporting the earlier observation that greater separation of cyclists from cars increases all three measures of effectiveness. The multi-use dummy coefficient was not substantially different from the protected bike lane coefficients, however it was still included separately in the model because the multi-use images excluded the effects of roadway characteristic variables.

The framing effect terms were significant in each model. These variables show sensitivity to the *comparative removal* of a perceived negative aspect (parking, or additional travel lane) that is not explained by the variables indicating the *absence* of that aspect alone. For example, when an image without parking was presented after an image with parking, it tended to receive a higher rating than if it were preceded by an image that also had no parking.

While the framing variables picked up the influence of multiple simultaneous changes from image to image, the “Parking” and “Four Lanes” variables represented the overall effects of roadway characteristics. The parking variable was significant in all models, indicating that the overall effect of parking was still significant, even after accounting for the strong impact of the removal of parking in the images affected by framing. The variable for the number of traffic lanes alone was not significant, though the significance of the framing variables indicates at least a situational effect when the number of lanes presented in the figure changes.

4.2.1 Alternative to Regression

Common practice in early model development is to start with a simple linear regression model and gradually increase the complexity. Although the dependent variables of perceived safety, comfort and willingness to try are ordinal Likert-type variables, linear regression is found to be reasonably robust for 5 levels of ordinal values.

An ordered logistic regression model was also estimated for each dependent variable, and is presented in Table 4-4. This type of model relaxes the assumption of linear regression that a difference of one unit in the dependent variable always means the same thing (e.g. that the difference between a 3 and a 4 is the same as the difference between a 2 and a 3). Otherwise, the model is conceptually similar to the linear regression model. All variables maintain their general significance level between the two models, and the coefficients have the same comparative relationship to each other.

Table 4-4 Ordered Logistic Regression for Expressed Comfort, Safety, and Willingness to Try by Infrastructure Characteristics

Variable	Comfort			Safety			Willingness to Try		
	Coefficient		P	Coefficient		P	Coefficient		P
Intercept 1/2	-1.82	***	<0.001	-1.37	***	<0.001	-1.08	***	<0.001
Intercept 2/3	-0.54	***	<0.001	-0.01		0.844	-0.32	***	<0.001
Intercept 3/4	0.71	***	<0.001	1.12	***	<0.001	0.51	***	<0.001
Intercept 4/5	2.49	***	<0.001	2.94	***	<0.001	1.93	***	<0.001
Bicycle Infrastructure Types									
Bike Lane (BL)	0.59	***	<0.001	0.72	***	<0.001	0.38	***	<0.001
Buffered BL (BB)	1.18	***	<0.001	1.41	***	<0.001	0.74	***	<0.001
One-way Protected	2.29	***	<0.001	2.82	***	<0.001	1.56	***	<0.001
Two-way Protected	2.01	***	<0.001	2.44	***	<0.001	1.30	***	<0.001
Multi-use	2.21	***	<0.001	2.63	***	<0.001	1.61	***	<0.001
Roadway Characteristics									
Parking	-0.43	***	<0.001	-0.40	***	<0.001	-0.23	***	<0.001
Four Lanes	0.03		0.554	0.09		0.071	-0.04		0.412
Framing Effects									
BL-No Parking	0.67	***	<0.001	0.75	***	<0.001	0.55	***	<0.001
BBL-No Parking	0.36	***	<0.001	0.54	***	<0.001	0.30	**	0.002
BL-Two Lanes	0.45	***	<0.001	0.56	***	<0.001	0.28	*	0.019
# of Responses	6743			6723			6664		

*Significant at P = 0.050 or better
**Significant at P = 0.010 or better
***Significant at P < 0.001

Although ordered logistic regression does not require constant interval differences to be maintained, it does impose the restrictive requirement that the impact of a given explanatory variable does not differ by level of the dependent variable—i.e., the slope coefficients are constant across level. This is called the parallel lines assumption, and its validity is tested using the Brant Parallel Lines Test. This test was conducted on the three ordered logistic models, and the results are presented in Table 4-5. A low P value in this test for either the combined model or for a particular variable indicates violation of the parallel lines assumption. The low P values obtained show that the bicycle infrastructure variables violate this assumption, indicating that a generalized ordered logit or multinomial logit model may be more appropriate than the ordered logit. These models are currently being investigated in more detail. However, since the models are still in the exploratory process the linear regression model was carried further due to easier interpretability.

Table 4-5 Brant Parallel Line Test Results for Ordered Logistic Regression Models for Comfort, Safety, and Willingness to Try

Variable	Comfort			Safety			Willingness to Try		
	χ^2	df	P	χ^2	df	P	χ^2	df	P
Combined Model	95.6	30	<0.01	108.9	30	<0.01	99.7	30	<0.01
Bicycle Infrastructure Types									
Bike Lane (BL)	8.6	3	0.04	12.3	3	0.01	10.6	3	0.01
Buffered BL (BB)	12.6	3	0.01	14.6	3	<0.01	7.2	3	0.06
One-way Protected	8.8	3	0.03	5.2	3	0.16	7.1	3	0.07
Two-way Protected	17.6	3	<0.01	41.0	3	<0.01	22.9	3	<0.01
Multi-use	15.7	3	<0.01	23.7	3	<0.01	7.8	3	0.05
Roadway Characteristics									
Parking	15.4	3	<0.01	11.5	3	0.01	6.6	3	0.09
Four Lanes	1.0	3	0.80	1.4	3	0.70	17.3	3	<0.01
Framing Effects									
BL-No Parking	1.8	3	0.62	2.3	3	0.52	5.8	3	0.12
BBL-No Parking	2.1	3	0.55	2.4	3	0.50	0.0	3	0.99
BL-Two Lanes	2.8	3	0.43	4.6	3	0.20	2.8	3	0.43

4.3 Additional Influence of Sociodemographic Traits

The influence of sociodemographics on the perceptions of interest is critically important to controlling for non-response bias and to understanding what populations would be served with the implementation of various types of infrastructure. Therefore, the previous models were supplemented with sociodemographic data, as presented in Table 4-6. For the few cases where this information was not reported by the survey respondent, data obtained from targeted marketing sources was used as an estimate.

In all three models, education and age were significant, with consistent signs between models. However, both of these coefficients were comparatively larger in the willingness to try model. Older individuals tended to express lower perceived comfort and safety, and even more so for willingness to try. Individuals with higher levels of education tended to express greater perceived comfort and safety, and even more so for willingness to try.

The number of vehicles per licensed driver (at the household level, capped at 1.0) was significant in the comfort and willingness to try models. This variable measures individuals' access to an automobile in their home, and indicates that those with increased access tend to view a given infrastructure as less comfortable and as something they would be less willing to try.

The coefficients for driver's license and child in home were significant only in the safety model. The positive coefficient for driver's license may indicate that those with a license feel more control over the safety of the roadway in general. The child in home coefficient was negative, which indicates that those who have a child in their home tend to view bicycling infrastructure as less safe than those who do not. This could be the result of considering cycling with their children or of an increased attention to safety due to the responsibilities of raising children.

Coefficients on the female and African-American variables were significant only in the willingness to try model, and were negative in both cases. This indicates that these two subsets of the population may be less willing than others to try a given infrastructure configuration, even if their perceptions of its safety and comfort are similar to those of others. This could be due to important factors other than safety and comfort, and may serve as the basis for further analysis.

Table 4-6 Linear Regression for Expressed Comfort, Safety, and Willingness to Try by Infrastructure and Individual Characteristics

Variable	Comfort			Safety			Willingness to Try		
	Coefficient		P	Coefficient		P	Coefficient		P
Constant	3.09	***	<0.001	2.55	***	<0.001	3.59	***	<0.001
Bicycle Infrastructure Types									
Bike Lane	0.40	***	<0.001	0.47	***	<0.001	0.32	***	<0.001
Buffered Bike Lane	0.77	***	<0.001	0.90	***	<0.001	0.59	***	<0.001
One-way Protected	1.39	***	<0.001	1.69	***	<0.001	1.15	***	<0.001
Two-way Protected	1.21	***	<0.001	1.47	***	<0.001	1.03	***	<0.001
Multi-use	1.30	***	<0.001	1.55	***	<0.001	1.19	***	<0.001
Roadway Characteristics									
Parking	-0.27	***	<0.001	-0.25	***	<0.001	-0.16	***	<0.001
Four Lanes	0.03		0.477	0.04		0.103	-0.03		0.441
Framing Effects									
BL-No Parking	0.41	***	<0.001	0.50	***	<0.001	0.44	***	<0.001
BBL-No Parking	0.23	***	<0.001	0.34	***	<0.001	0.26	***	<0.001
BL-Two Lanes	0.26	***	<0.001	0.31	***	<0.001	0.19	*	0.038
Sociodemographics									
Age	-0.004	***	<0.001	-0.004	***	<0.001	-0.01	***	<0.001
Education	0.04	***	<0.001	0.03	**	0.001	0.09	***	<0.001
Vehicles Per Driver	-0.16	**	0.003				-0.38	***	<0.001
Driver's License				0.18	***	<0.001			
Child in Home				-0.08	*	0.033			
Female							-0.29	***	<0.001
African-American							-0.08	*	0.047
# of Responses	6159			6529			6086		
R^2	0.201			0.248			0.153		
Adj R^2	0.199			0.246			0.151		

*Significant at P = 0.050 or better

**Significant at P = 0.010 or better

***Significant at P < 0.001

Inclusion of sociodemographic variables noticeably improved the goodness of fit of the models; the resulting R^2 measures of 0.153 to 0.248 are typical for disaggregate regression models of travel-related variables. Sociodemographic characteristics seemed to play a larger role in the willingness to try model than for the other two perceptions, as seen by the increase in the R^2 value from 0.093 (TABLE 3) to 0.153 (compared to increases of 0.026 and 0.016, respectively, for the other two models). This indicates that individual characteristics are more influential to potential users' willingness to use a certain type of infrastructure than to their perceptions of whether it is safe or comfortable in general. Although income and household size distributions for the sample were different from those of the population, neither variable was significant on its own in these models. However, income is often highly correlated with vehicle ownership, and the variable measuring the number of vehicles per driver in the household takes a portion of the interaction of these variables with household size into account.

4.4 Rider Type Segments

Another key aspect of understanding infrastructure development is the rider types that would be attracted to various infrastructure types. A segmented model was developed to investigate how the influence of the other explanatory variables differs by rider group. The four rider statuses created are potential rider, recreational, utilitarian, and those that cannot bike. The criteria for inclusion in one of these categories comes from the responses to questions regarding bicycling confidence, cycling distances for recreation/utilitarian purposes, and cycling trip frequency for commute/other purposes. The four segments and their criteria are:

1. Potential cyclist (N=700)—those who report zero miles of cycling per month, but report being able to ride a bike, regardless of confidence level.
2. Recreational cyclist (N=166)—those who bike a non-zero distance per month, but bike less than once a month *and* less than a mile a week, on average, for utilitarian purposes.
3. Utilitarian cyclist (N=84)—those who bike at least once a month *or* at least a mile a week, on average, for utilitarian purposes.
4. Cannot bike (N=163)—those who state that they cannot ride a bicycle.

The potential cyclist population was used as the base, and incremental-difference coefficients are reported for segments with significant differences from the base group. Not all segments were significantly different from the base in each model.

Each segmented model started from the previously reported regression models for comfort, safety, and willingness to try, respectively. Dummy variables were introduced for the "recreation", "utilitarian", and "cannot bike" segments, using the "potential cyclists" as the base. The incremental effects for each segment were estimated using interaction terms between the main effect explanatory variables and the segment dummy variables, piece-wise removing insignificant variables (constraining them to be 0). Insignificant variables were included in cases with borderline significance, where a main effect was insignificant but an associated interaction effect was significant, and/or in cases where the coefficient is necessary for interpretation of a similar variable, such as for different types of bicycle infrastructure. The segmented models for expressed comfort, safety, and willingness to try are presented in Table 4-7.

Table 4-7 Linear Regressions for Expressed Comfort, Safety, and Willingness to Try Including Incremental Effects of Cyclist Segments (Base Segment: Potential Cyclists)

Variable	Comfort			Safety			Willingness to Try		
Main Effects	Coefficient		P	Coefficient		P	Coefficient		P
Constant	3.14	***	<0.001	2.64	***	<0.001	3.74	***	<0.001
Recreation (2)	0.17	***	<0.001	0.15	***	<0.001	-0.65	**	0.004
Utilitarian (3)	-0.54	*	0.012	-0.86	***	<0.001	-0.20		0.428
Unable (4)	-0.09	*	0.031	-0.01		0.858	-1.89	***	<0.001
Bicycle Infrastructure Types									
Bike Lane (BL)	0.40	***	<0.001	0.47	***	<0.001	0.32	***	<0.001
Buffered BL (BB)	0.76	***	<0.001	0.90	***	<0.001	0.59	***	<0.001
One-way Protected	1.39	***	<0.001	1.72	***	<0.001	1.15	***	<0.001
Two-way Protected	1.22	***	<0.001	1.50	***	<0.001	1.02	***	<0.001
Multi-use	1.30	***	<0.001	1.56	***	<0.001	1.19	***	<0.001
Roadway Characteristics									
Parking	-0.29	***	<0.001	-0.28	***	<0.001	-0.21	***	<0.001
Four Lanes	0.02		0.438	0.05		0.099	-0.05		0.152
Framing Effects									
BL-No Parking	0.41	***	<0.001	0.51	***	<0.001	0.44	***	<0.001
BB-No Parking	0.24	***	<0.001	0.36	***	<0.001	0.25	***	<0.001
BL- Two Lanes	0.24	**	0.001	0.29	***	<0.001	0.18	*	0.043
Sociodemographics									
Age	-0.003	***	<0.001	-0.004	***	<0.001	-0.009	***	<0.001
Education	0.03	**	0.002	0.02	*	0.032	0.03	*	0.012
Vehicles per Driver	-0.23	***	<0.001	-0.17	**	0.007	-0.48	***	<0.001
Child in Home				-0.05		0.236			
Driver's License				0.22	*	0.015			
Female							-0.19	***	<0.001
African American							-0.16	***	<0.001

Table 4-7 Linear Regressions for Expressed Comfort, Safety, and Willingness to Try Including Incremental Effects of Cyclist Segments (continued)

Variable	Comfort			Safety			Willingness to Try		
Incremental Effects	Coefficient		P	Coefficient		P	Coefficient		P
Utilitarian Segment									
(3)*BL				0.31	*	0.041			
(3)*BB				0.36	*	0.026			
(3)*One-way Protected				0.44	*	0.030			
(3)*Two-way Protected				0.40		0.072			
(3)*Multi-use				0.59	**	0.002			
(3)*Parking	0.20	*	0.046	0.29	**	0.009			
(3)*Age	0.009	**	0.008	0.006		0.095	0.009	*	0.032
(3)*Vehicles/Driver	0.44	**	0.010	0.44	*	0.014	0.50	*	0.016
(3)*Child in Home				-0.27	*	0.036			
Cannot Bike Segment									
(4)*Child in Home				-0.25		0.082			
(4)*Parking							0.37	***	<0.001
(4)*Four Lanes							0.24	*	0.014
(4)*Age							0.009	*	0.015
(4)*African American							0.62	***	<0.001
(4)*Vehicles/Driver							0.40	*	0.026
Recreation Segment									
(2)*Age							0.008	**	0.009
(2)*Education							0.15	***	<0.001
# of Responses	6038			5982			5966		
R^2	0.212			0.268			0.206		
Adj R^2	0.210			0.265			0.203		

*Significant at P = 0.050 or better

**Significant at P = 0.010 or better

***Significant at P < 0.001

The primary differences uncovered by the expressed comfort model are the incremental effects for utilitarian cyclists. Compared to the rest of the population, utilitarian cyclists were less likely to express discomfort due to the presence of parking. Age is a net-positive coefficient for the utilitarian group, implying that older utilitarian cyclists are more likely than others to rate infrastructure as comfortable.

Like the previous model, most of the differences for the expressed safety come from the utilitarian group. Each infrastructure variable is positive for utilitarian cyclists, indicating that although all groups see each added degree of protection as an increase in safety, the group that cycles most perceives an even greater increase in safety. The parking coefficient was positive for utilitarian cyclists, with a similar magnitude to the (negative) base parking coefficient, indicating that utilitarian cyclists do not view on-street parking as significantly unsafe like the rest of the sample does. The coefficients for the variable measuring the presence of children in the home for the utilitarian and unable groups were significantly (or borderline significantly) negative, while the base coefficient became insignificant in this model, indicating that the negative impact on perceived safety associated with the presence of a child in the home is driven by these two groups.

For the willingness to try model, the only roadway characteristics to be significant in any segmentation were the parking and four lanes variables for those unable to bike. Both were positive, with higher magnitudes than the negative base coefficients. This segregation likewise allows the coefficient for the rest of the population to be more negative for the parking variable, while the four-lane variable inches closer to significantly negative. This implies that the stated preferences of those who can’t bike may contradict those of the rest of the population in terms of willingness to try cycling in the presence of parking and additional traffic lanes. Although the change in sign for these coefficients may seem unexpected, the rather large magnitude of the negative constant term for that group indicates that this group is still substantially less willing to try cycling in comparison to the other groups. The coefficients for age are all significant and have similar magnitudes, with only the base being negative. This indicates that age is a deterrent for those in the potential cyclist group but does not have a significant effect among the recreation, utilitarian, and unable groups.

4.5 Chapter Summary

This chapter discusses the findings of the first-wave survey (N=1,178) deployed in six communities in Alabama and Tennessee, where cycling is not widely adopted. Consistent with previous studies, the survey results suggest that perceived safety and comfort are strongly related to a user’s willingness to bike. Respondents rated infrastructure having a higher degree of separation from drivers more positively, with protected bike lanes and multi-use paths being the best. Parking was a clear deterrent for all measures of preference, though the effects of the number of traffic lanes are mixed. Protected bike lanes seemed effective in reducing the negative effects of roadway characteristics.

User characteristics were significant in modeling respondents' perceptions of being comfortable, safe, and willing to try biking. Sociodemographic information was more influential in predicting willingness to try, indicating that even when safety and comfort are similarly perceived across population segments, willingness to try can differ. On average, older respondents responded more negatively on all measures as opposed to younger respondents.

The key findings presented in this chapter come from the segmented models, which indicate that perceptions of infrastructure characteristics can be substantially different among different rider types. Regular utilitarian cyclists overwhelmingly viewed separated facilities as safer than sharrows, and even more so than the rest of the sample, but were less daunted by the presence of parking. Occasional/recreational cyclists' preferences were surprisingly similar to those of potential cyclists, with no significant difference for perceived comfort and safety, and only education and age being significant for willingness to try. Those who are not able to bike did not differ significantly from the base of potential cyclists except in the willingness to try model, though this segment may be of less interest.

The limitations of this analysis include the hypothetical nature of stated preference studies. Although Birmingham and Chattanooga have a representative amount of bike infrastructure and Northport has several trails, most residents in our sample likely would not have seen many of the presented infrastructure types, adding to the hypothetical challenges in this study. Further work will include a follow-up study of these same sites with the intent of linking stated and revealed preferences.

The findings from this study raise a much-needed voice from areas of the U.S. without a strong cycling presence. This study includes only a handful of locations from one geographic region, but the survey used in this study was written for general application in other locations.

CHAPTER 5. THE ROLE OF ATTITUDES IN PERCEPTIONS OF BICYCLE FACILITIES: A LATENT-CLASS APPROACH

This chapter expands upon the work in the previous chapter from simply investigating the impact of bicycle facility attributes on perceptions and preferences for bicycling infrastructure to analyzing the role of attitudinal factors in perceptions of and preferences for bicycle facilities, and how these attitudes can impact the way bicycle facility and roadway characteristics shape perceptions and preferences, differently for potential users. Past research has primarily focused on more visible criteria for determining taste variations, such as sociodemographics or bicycling experience, without also exploring attitudinal factors, which may prove useful in explaining the reasons for such variations. There are a variety of ways to account for the heterogeneity of preferences and perceptions among different groups (Rossetti et al. 2018). Félix et al. (2017) discussed some of these modeling strategies, including segmented models and latent-class models. They found that most useful segmentations include classes similar to the following: proficient riders, willing but not convinced, and noncyclists. Clark et al. (2019), along with Sanders and Judelman (2018), use bicycling frequency to determine segments. Geller (2006) along with Dill and McNeil (2013) segmented the population into four different cyclist types based on confidence level: strong and fearless, enthused and confident, interested but concerned, and no way, no how. Handy et al. (2010) segregate based on both bike ownership and bicycling frequency. This research is also novel in its application of latent classes rather than deterministic segments, to explore taste heterogeneity. This chapter has been submitted for publication in a high-quality journal as Clark, Mokhtarian, Circella, and Watkins, “The Role of Attitudes in Perceptions of Bicycle Facilities: A Latent-Class Regression Approach”.

5.1 Survey Data

The data for the analysis in this chapter comes from the first-wave survey of current and potential cyclists from all ten of the sampled communities, though this analysis does not distinguish between control and treatment sites. The ten communities and their respective number of respondents were:

- Opelika, Alabama (AL), population 29,101 (N=145);
- Anniston, AL, population 22,441 (N=134);
- Chattanooga, Tennessee (TN), population 174,749 (N=184);
- Northport, AL, population 24,611 (N=191);
- Talladega, AL, population 15,882 (N=62);

- Birmingham, AL, population 211,875 (N=233); and
- Atlanta, Georgia (GA), population 455,589 (N=1,208); including four different neighborhoods:
    - Eastside BeltLine Extension (N=415),
    - Westside BeltLine (N=184),
    - Grant Park (N=451), and
    - South Atlanta (N=158).

There were 2,558 total responses to the survey (constituting a response rate of 6.2%), with 2,157 (including 571 that completed the online version) remaining after data cleaning and removing those who stated they were unable to bike. While complete sociodemographic statistics were included in Chapter 3, a brief summary of applicable sociodemographics for this pooled pooled sample is presented in Table 5-1. The largest income group was the wealthiest group, with slightly less than half of respondents reporting a household income less than $75,000. Females were somewhat more represented than males, as is typical for many surveys administered by mail. All age groups were represented among respondents, with the largest group being those between 35 and 49. The majority of respondents were White/Caucasian, followed by those who identified as Black/African American, with small amounts of all other races/ethnicities being reported. More than half of respondents described themselves as "very confident" in riding a bike, which seems surprising, but may be an indication of respondents overstating how confident they really are in riding a bike, or simply responding in the abstract (e.g., thinking about biking on the low-traffic streets of one's childhood neighborhood). It may also reflect a pro-biking response bias remaining even after efforts to minimize it.

Table 5-1 Distribution of Demographics for Survey Respondents

		Responses	% of Respondents	% of Pooled Population*
Household Income	$15,000 or less	165	7.6%	27%
	$15,001 - $30,000	180	8.3%	21%
	$30,001 - $50,000	241	11%	18%
	$50,001 - $75,000	327	15%	14%
	$75,001 - $100,000	280	13%	8.1%
	$100,001 - $125,000	205	10%	5.0%
	More than $125,000	493	23%	7.8%
	Prefer not to answer	266	12%	NA
Gender	Female	1,222	57%	56%
	Male	914	42%	44%
	Prefer not to answer	18	0.8%	NA
	Other	3	0.1%	NA
Respondent Age	18-34	542	25%	40%
	35-49	646	30%	25%
	50-64	593	27%	22%
	65+	376	17%	13%
Race/Ethnicity**	White / Caucasian	1466	68%	39%
	Black / African American	527	24%	55%
	Hispanic / Latino	42	1.9%	4.9%
	American Indian / Native American	37	1.7%	--
	Asian / Pacific Islander	51	2.4%	--
	Other	44	2.0%	5.5%
	Prefer not to answer	36	1.7%	NA
Bike Confidence	Not very confident	421	20%	NA
	Somewhat confident	618	29%	NA
	Very confident	1118	52%	NA

*From ACS estimates, except for gender, which comes from targeted marketing data for purchased addressees

**Respondents were allowed to mark more than one (sum of percentages may exceed 100%)

5.2 Results and Discussion

In this section, regression models on the sample as a whole are presented first for benchmarking purposes. Then, latent class regression models that allow the regression coefficients to differ by segment are presented, followed by summarization and discuss some of the key findings.

5.2.1 Linear Regression Models

Linear regression models were estimated using responses to the infrastructure images. Although treating Likert-type data as continuous variables technically violates some assumptions associated with linear regression models, such models are commonly viewed as being robust with respect to violations of the assumptions, and ordinal data can serve as a reliable approximation to a continuous scale when there are four or more response levels, as is the case here (Bentler and Chou 1987). Much empirical research over the years has used Likert-type data with parametric methods such as regression, and a review of the progression of this research assures scholars that such methods can be employed in these cases "with no fear of 'coming to the wrong conclusion' " (Norman 2010, pp. 631). Still, alternative model forms (multinomial logit) were also estimated. As the specifications of these models were not drastically different, the parsimony and ease of interpretability of the simpler regression models were preferred and are the focus of the body of this chapter, though specifications for the alternative models are presented.

Models were built separately for each of the three items: perceived comfort, perceived safety, and willingness to try, based initially on those presented in the previous chapter. Dummy variables were included as explanatory variables for both bicycle facility types (such as bike lanes) and roadway characteristics (such as on-street parking), along with dummy variables to control for framing effects due to the order of presentation of images. Attitudinal factors and sociodemographics were also included as explanatory variables. Cluster-robust standard errors were employed throughout, in view of the fact that each individual rated up to six infrastructure configurations for each dependent variable. The resultant models are presented in Table 5-2.

Table 5-2 Linear Regression Models for Perceived Comfort, Perceived Safety, and Willingness to Try Biking by Infrastructure and Individual Characteristics

Variable	Comfort			Safety			Willingness to Try		
# of Responses	12,974			12,964			13,102		
R^2	0.276			0.323			0.354		
	Coefficient		P	Coefficient		P	Coefficient		P
Intercept	2.77	***	<0.001	2.47	***	<0.001	3.44	***	<0.001
Bicycle Facility Types									
Bike Lane (BL)	0.53	***	<0.001	0.58	***	<0.001	0.35	***	<0.001
Buffered BL	0.92	***	<0.001	1.08	***	<0.001	0.65	***	<0.001
One-way Protected BL	1.58	***	<0.001	1.93	***	<0.001	1.20	***	<0.001
Two-way Protected BL	1.39	***	<0.001	1.71	***	<0.001	1.05	***	<0.001
Multi-use Path	1.40	***	<0.001	1.68	***	<0.001	1.13	***	<0.001
Roadway Characteristics									
Parking	-0.22	***	<0.001	-0.23	***	<0.001	-0.21	***	<0.001
Four Lanes	-0.037		0.200	-0.009		0.740	-0.091	**	0.005
Framing Effects									
Buffered BL, No Parking	0.21	***	<0.001	0.32	***	<0.001	0.16	***	<0.001
BL, No Parking	0.34	***	<0.001	0.47	***	<0.001	0.28	***	<0.001
BL, Two Lanes	0.21	***	<0.001	0.27	***	<0.001	0.16	**	0.001
Attitudinal Factors									
Car Preference	-0.048	***	<0.001	-0.046	***	<0.001	-0.16	***	<0.001
Bike Enjoyment	0.18	***	<0.001	0.14	***	<0.001	0.39	***	<0.001
Anti-Exercise	-0.047	***	<0.001	-0.038	**	0.003	-0.084	***	<0.001
Risk Tolerance	0.052	***	<0.001	0.033	**	0.005	0.079	***	<0.001
Sociodemographics									
Driver's License	0.19	*	0.012	0.20	*	0.010			
Age (in 10's of years)	-0.028	**	0.006	-0.029	**	0.004	-0.083	***	<0.001
Female							-0.20	***	<0.001
White / Caucasian							0.19	***	<0.001
*Significant at 0.050									
**Significant at 0.010									
***Significant at 0.001									

The coefficients for infrastructure characteristics have the expected signs. Bicycle facility type coefficients are all positive, indicating that each option was preferable to the base type, sharrow. The magnitudes of these coefficients are generally in the expected order, with bike lanes being smallest, buffered bike lanes being the next, and both protected bike lanes and multi-use paths being the highest. Parking was a deterrent in each model, while the impact of the number of lanes was largely insignificant, except in the willingness to try model where it was negative, but less so than that of the parking coefficient.

The attitudinal factor and sociodemographic coefficients are also in the expected directions. A preference for automobiles was associated with lower scores for each model, but more so for the willingness to try model. The coefficients of the other attitudinal factors were also greater in magnitude in the willingness to try model than in the perceived comfort and perceived safety models, though to a lesser extent. Bike enjoyment was the strongest factor in each model, with the positive coefficient supporting the expected association of a stronger enjoyment of biking with more positive perceptions of bicycle facilities. The negative coefficient of the anti-exercise factor indicates that the existence of anti-exercise sentiments was associated with less positive perceptions of bicycle facilities, while the positive coefficient of the risk tolerance factor indicates that a greater acceptance of risk is associated with more favorable perceptions of bicycle facilities. The negative coefficients for age imply that older individuals tended to view roadways as less safe, less comfortable, and something they were less inclined to try than younger people. Holding a driver's license was associated with a greater degree of expressed comfort and safety, which may signify a sense of self-efficacy or being in control contributing to feelings of comfort and safety. All else equal, women tended to be less willing to try a facility than men, while those identifying as White / Caucasian had generally positive responses.

5.2.2 Latent Class Linear Regression Models

While the models presented in the previous section are informative regarding the average impacts of certain variables on preferences and perceptions, they are limited in their ability to explain taste variations among different groups. To address potential taste heterogeneity, a different model structure must be chosen that can allow explanatory variable coefficients to differ among groups. Deterministically segmented models such as those from Clark et al. (2019) and Wang and Akar (2018) are useful for assessing differences in preferences among predetermined segments; however, latent class models go a step farther by allowing the model to identify the most ideal differentiation of classes from the standpoint of the ability to predict the dependent variable. Latent class models were estimated on the same dependent variables, with bicycle facility type, roadway characteristics, and framing effect variables being included in the models for the dependent variable, and attitudinal and sociodemographic variables being included in the class membership models. A wide array of attitudinal and sociodemographic variables was tested in preliminary class membership model estimations, with insignificant or collinear variables being removed stepwise. Models with differing numbers of classes ranging from two classes to over 11 classes were considered. AIC and BIC measures improved with more classes up to 11, however, there are no hard-and-fast rules for determining the "ideal" number of classes. I balanced statistical measures against parsimony and interpretability. Ultimately, three classes were chosen for each of the models in this section as it provided the best balance between simplicity and uncovering new information.

The linear latent class model for comfort is presented in Table 5-3 and Table 5-4. The model identifies three classes. Class 1 is characterized by higher average car preference factor scores and lower bike enjoyment scores. Conversely, Classes 2 and 3 are characterized by higher bike enjoyment scores and lower car preference scores. The latter two classes differ on their scores for risk tolerance, with Class 3 being much higher than Class 2, on average. This distinction between Classes 2 and 3 sheds light on two potential bicyclist subgroups that may not otherwise be obvious: confident and concerned. The added benefit of this delineation is the discovery that, for perceived comfort, the difference between the cautious and confident groups are almost entirely in their risk tolerance, while their enjoyment of biking is similar.

The bicycle facility type coefficients are remarkably different between classes. The pro-car Class 1, which contains about half of the sample, has coefficients similar to the average effects reported in Table 5-2. The facility type coefficients for the bike-enthused but risk-cautious Class 2 are much higher than the average effects reported previously, indicating that the presence of any separated facility is profoundly beneficial in producing stronger perceptions of comfort than a sharrow among the members of this class. On the other hand, the bike-enthused and confident Class 3 had rather small coefficients for bicycle facilities. This indicates that for this group, the nature of the facility does not seem to be as important in shaping perceptions of comfort, though the large intercept term indicates that the perceptions of comfort are already rather high on average anyway.

Table 5-3 Latent-Class Linear Models for Perceived Comfort Outcome Model with Infrastructure Characteristics as Predictors

Model for Perceived Comfort						
	Class 1 Pro-car	Class 2 Pro-bike/ Risk-neutral	Class 3 Pro-bike/ Risk-embracing		Overall	
R^2 Value#	0.255	0.715	0.153		0.555	
Class Share	0.498	0.263	0.239		1.000	
		Coefficients			P##	P##(=)
Intercept	2.57	2.18	4.14	***	<0.001	<0.001
Bicycle Facility Types						
Bike Lane (BL)	0.21	1.62	0.11	***	<0.001	<0.001
Buffered BL	0.54	2.05	0.33	***	<0.001	<0.001
One-way Protected BL	1.42	2.63	0.63	***	<0.001	<0.001
Two-way Protected BL	1.32	2.55	0.56	***	<0.001	<0.001
Multi-use Path	1.28	2.52	0.56	***	<0.001	<0.001
Roadway Characteristics						
Parking	-0.30	-0.09	-0.04	***	<0.001	<0.001
Four Lanes	-0.031	0.005	-0.020		0.830	0.710
Framing Effects						
Buffered BL, No Parking	0.54	0.18	0.11	***	<0.001	<0.001
BL, No Parking	0.62	0.16	0.13	***	<0.001	<0.001
BL, Two Lanes	0.12	0.12	0.12	**	0.002	--###

*Significant at 0.050
**Significant at 0.010
***Significant at 0.001

#R^2 for latent class regression in LatentGOLD is calculated as $R^2 = 1 - \frac{Error(model)}{Error(baseline)}$, where Error(model) is defined as the average of the squared differences between the observed values and the posterior-probability weighted expected values and Error(baseline) is the average of the squared differences between the observed values and the predictions in the intercept only model

##P refers to the P-value for the Wald test of significance of the average effect across all classes

##P (=) refers to the P-value for a test of equality of coefficients across all three classes

###Constrained to be equal since initial model estimations indicated no significant differences across classes

Table 5-4 Latent-Class Linear Models for Perceived Comfort Class-Membership Model with Individual Characteristics as Covariates

Class Membership Model	Coefficients					Class Mean		
	Class 1 Pro-car	Class 2 Pro-bike/ Risk-neutral	Class 3 Pro-bike/ Risk-embracing		P	Class 1	Class 2	Class 3
Intercept	0	-1.07	-1.87	***	<0.001	--	--	--
Current Cyclist	0	0.11	0.54	**	0.001	0.27	0.46	0.56
Car Preference	0	-0.20	-0.09	**	0.003	0.14	-0.28	-0.14
Bike Enjoyment	0	0.45	0.36	***	<0.001	-0.11	0.50	0.55
Risk Tolerance	0	-0.001	0.20	***	<0.001	-0.09	0.06	0.48
Anti-exercise	0	-0.20	-0.14	***	<0.001	0.05	-0.36	-0.29
Income over $75,000	0	0.39	0.011	*	0.012	0.45	0.62	0.54
Bike Confidence†	0	0.011	0.22		0.072	3.20	3.42	3.57

*Significant at 0.050
**Significant at 0.010
***Significant at 0.001

† Expressed confidence: 2=not very confident, 3=somewhat confident, 4=very confident

A similar latent class model was estimated with perceived safety as the dependent variable, presented in Table 5-5 and Table 5-6. As with the comfort models, Class 1 tends to prefer automobiles, Class 3 consists of risk-embracing pro-cyclists, and Class 2 is characterized by pro-cyclist attitudes but a drastically lower risk-taking tendency. The similarities between the perceived comfort and perceived safety models provide further evidence of the distinction among pro-cyclists with varying degrees of risk tolerance. Specifically, the magnitudes of the bicycle facility type coefficients are comparable to those in the models for perceived comfort, with the pro-bike/risk-cautious Class 2 having much larger coefficients. The large intercept of the pro-bike/risk-embracing Class 3 confirms the positive perceptions that those in this group have about bicycling facilities in general.

The main difference between the two models is that the size of Class 3 decreased from 23.9% in the comfort model to 15.6% in the perceived safety model, while the size of Class 2 increased from 26.3% in the comfort model to 32.4% in the perceived safety model. These differences suggest that those on the more conservative edge of the pro-bike/risk-embracing group were somewhat more likely to behave more like the more cautious Class 2 than the risk-embracing Class 3 in perceptions of safety as opposed to comfort. Bicycle confidence, which was marginally significant in the perceived comfort models, was substantially less significant in this model, and thus was dropped in favor of parsimony. The lack of significance of this variable is an interesting finding in itself, indicating that constructs regarding attitudes towards bicycling and risk management seem to play much larger roles in shaping perceptions than the expressed bicycling confidence of respondents, particularly for matters of perceived safety.

Table 5-5 Latent-Class Linear Models for Perceived Safety Outcome Model with Infrastructure Characteristics as Predictors

Model for Perceived Safety						
	Class 1 Pro-car	Class 2 Pro-bike/ Risk-neutral	Class 3 Pro-bike/ Risk-embracing		Overall	
R^2 Value#	0.320	0.690	0.175		0.575	
Class Share	0.520	0.324	0.156		1.000	
		Coefficients			P##	P##(=)
Intercept	2.38	2.17	4.11	***	<0.001	<0.001
Bicycle Facility Types						
Bike Lane (BL)	0.22	1.41	0.15	***	<0.001	<0.001
Buffered BL	0.60	2.02	0.47	***	<0.001	<0.001
One-way Protected BL	1.71	2.64	0.81	***	<0.001	<0.001
Two-way Protected BL	1.61	2.62	0.56	***	<0.001	<0.001
Multi-use Path	1.49	2.48	0.53	***	<0.001	<0.001
Roadway Characteristics						
Parking	-0.29	-0.14	-0.08	***	<0.001	0.014
Four Lanes	-0.069	-0.035	-0.041		0.260	0.790
Framing Effects						
Buffered BL, No Parking	0.68	0.25	0.08	***	<0.001	<0.001
BL, No Parking	0.69	0.37	0.09	***	<0.001	<0.001
BL, Two Lanes	-0.02	0.20	0.18	**	0.001	0.039

*Significant at 0.050

**Significant at 0.010

***Significant at 0.001

#R^2 for latent class regression in LatentGOLD is calculated as $R^2 = 1 - \frac{Error(model)}{Error(baseline)}$, where Error(model) is defined as the average of the squared differences between the observed values and the posterior-probability weighted expected values and Error(baseline) is the average of the squared differences between the observed values and the predictions in the intercept only model

##P refers to the P-value for the Wald test of significance of the average effect across all classes

##P (=) refers to the P-value for a test of equality of coefficients across all three classes

Table 5-6 Latent-Class Linear Models for Perceived Safety Class-Membership Model with Individual Characteristics as Covariates

Class Membership Model	Coefficients					Class Mean		
	Class 1 Pro-car	Class 2 Pro-bike/ Risk-neutral	Class 3 Pro-bike/ Risk-embracing		P	Class 1	Class 2	Class 3
Intercept	0	-0.84	-1.41	***	<0.001	--	--	--
Current Cyclist	0	0.06	0.46	*	0.019	0.29	0.47	0.50
Car Preference	0	-0.22	-0.02	***	0.003	0.13	-0.31	-0.01
Bike Enjoyment	0	0.38	0.27	***	<0.001	-0.05	0.49	0.44
Risk Tolerance	0	-0.01	0.18	**	0.002	-0.05	0.08	0.42
Anti-exercise	0	-0.28	-0.14	***	<0.001	0.09	-0.41	-0.20
Income over $75,000	0	0.34	-0.15	**	0.005	0.45	0.62	0.48

*Significant at 0.050

**Significant at 0.010

***Significant at 0.001

A latent class model was also estimated for willingness to try cycling, presented in Table 5-7 and Table 5-8. While this model also identifies three classes, the nature of these classes has shifted. Class 1 includes those who are pro-bike and somewhat risk tolerant, while Class 2 includes those who prefer automobiles and Class 3 consists of extreme bike-enthusiasts and risk-embracers that respond as always willing to try bicycling. While either insignificant or borderline significant in the previous two models, expressed bicycling confidence was significant in this model, indicating an association between expressing great bicycling confidence and expressing great willingness to try cycling on a given infrastructure type. Women were most represented in Class 2 and least represented in Class 3, while the reverse was true for those identifying as White / Caucasian. The average age for Class 2 was 52, much higher than that of the lowest of 42 for Class 3. Not surprisingly, frequency of bicycling trips for non-commute purposes was highest among those in Class 3, with the average case reporting cycling several times a month, while the lowest frequency was for Class 2, with most cases reporting never cycling. It is interesting to note that in this model, the bicycling frequency variable was significant along with the dummy variable for being a current cyclist. This is in contrast to the previous two models where only one of the variables was significant when both were present (in which cases the current cyclist dummy variable was retained for simplicity's sake).

The facility coefficients for Class 3 are zero, while the intercept is 5, indicating that this class consists of the 9.6% of the sample that marked "Strongly agree" for willingness to try bicycling on every configuration presented to them. The R-squared of Class 3 is equal to zero, as there is no variation in the dependent variable left to explain after the class membership model has done its work of identifying this ultra-enthusiastic group.

The coefficients for the other two classes are rather moderate and intuitive, with car-aligned respondents having slightly higher coefficients for protected bike lanes and multi-use paths than bike-aligned respondents, and the reverse for bike lanes and buffered bike lanes, though this may be the case due to the large intercept value for Class 1, which is already very positive and does not provide much room to go substantially higher.

Table 5-7 Latent-Class Linear Models for Willingness to Try Biking Outcome Model with Infrastructure Characteristics as Predictors

Model for Willingness to Try						
	Class 1 Pro-bike/ Risk-tolerant	Class 2 Pro-car	Class 3 Always-willing		Overall	
R^2 Value#	0.275	0.210	0.000		0.560	
Class Share	0.467	0.437	0.096		1.000	
		Coefficients			P##	P##(=)
Intercept	3.61	2.18	5	***	<0.001	<0.001
Bicycle Facility Types						
Bike Lane (BL)	0.49	0.32	0	***	<0.001	<0.001
Buffered BL	0.74	0.62	0	***	<0.001	<0.001
One-way Protected BL	1.18	1.47	0	***	<0.001	<0.001
Two-way Protected BL	1.07	1.40	0	***	<0.001	<0.001
Multi-use Path	1.10	1.51	0	***	<0.001	<0.001
Roadway Characteristics						
Parking	-0.097	-0.24	0	***	<0.001	<0.001
Four Lanes	-0.053	-0.072	0		0.140	0.140
Framing Effects						
Buffered BL, No Parking	0.17	0.44	0	***	<0.001	<0.001
BL, No Parking	0.24	0.55	0	***	<0.001	<0.001
BL, Two Lanes	0.20	0.050	0	***	<0.001	<0.001

*Significant at 0.050

**Significant at 0.010

***Significant at 0.001

#R^2 for latent class regression in LatentGOLD is calculated as $R^2 = 1 - \frac{Error(model)}{Error(baseline)}$, where Error(model) is defined as the average of the squared differences between the observed values and the posterior-probability weighted expected values and Error(baseline) is the average of the squared differences between the observed values and the predictions in the intercept only model

##P refers to the P-value for the Wald test of significance of the average effect across all classes

##P (=) refers to the P-value for a test of equality of coefficients across all three classes

Table 5-8 Latent-Class Linear Models for Willingness to Try Biking Class-Membership Model with Individual Characteristics as Covariates

Class Membership Model	Coefficients					Class Mean		
	Class 1	Class 2	Class 3		P	Class 1	Class 2	Class 3
Intercept	0	0.19	-4.55	***	<0.001	--	--	--
Current Cyclist	0	-0.64	-0.14	***	<0.001	0.51	0.16	0.75
Car Preference	0	0.38	-0.12	***	<0.001	-0.24	0.38	-0.64
Bike Enjoyment	0	-0.64	0.13	***	<0.001	0.56	-0.33	0.86
Risk Tolerance	0	-0.13	0.10	**	0.003	0.23	-0.23	0.62
Anti-exercise	0	0.25	-0.12	***	<0.001	-0.34	0.19	-0.57
Bike Confidence†	0	-0.19	0.69	***	<0.001	3.50	3.05	3.83
Female	0	0.51	-0.06	***	<0.001	0.48	0.61	0.43
White/Caucasian	0	-0.63	0.06	***	<0.001	0.76	0.58	0.80
Age	0	0.017	-0.005	***	<0.001	44	52	42
Days Biked per Month††	0	-0.030	0.082	***	<0.001	1.84	0.38	5.46

*Significant at 0.050
**Significant at 0.010
***Significant at 0.001
†Expressed confidence: 2=not very confident, 3=somewhat confident, 4=very confident
††For non-commuting trips, reported as ordinal (Never, < once a month, 1-3 days a month, 1-2 days a week, 3-4 days a week, or >5 days/week) but converted to numeric

5.2.3 Multinomial Logit Latent Class Models

Although the linear models presented in the previous section can be considered sufficiently robust, multinomial logit models were also estimated for each of the dependent variables. These models are, in principle, more theoretically appropriate, although this rigor comes at the expense of a major loss of parsimony and interpretability due to the necessary estimation of additional parameters. To aid in parsimony, the "Disagree" and "Strongly disagree" responses were combined, along with the "Agree" and "Strongly agree" responses, reducing the choice set to three options.

The multinomial logit models presented in this subsection, while theoretically different from the previous models, appear to be reasonably similar in practice to their simpler counterparts. Consequently, these models serve as a sort of robustness check on the findings from the linear models previously discussed. However, despite the general similarities, there are some minor variations that may arise between the linear regression models and the multinomial logit models for each dependent variable. The existence of such variations does not necessarily discredit one model form or the other, but rather provides an alternative perspective on taste heterogeneity. One such variation is that for each of these models, the four-class solutions were deemed the most preferable for interpretation.

The multinomial logit model for comfort is presented in Table 5-9 and Table 5-10. In this model, Class 1 consists of those who are bike-inclined and risk tolerant, again representative of the enthused and confident class identified previously. Class 2 consists of those who are moderately bike-inclined but not risk tolerant, representative of the enthused but cautious. Where there was a single pro-car class in the linear models, there are two separate classes in this model, with Class 3 being characterized by those with a strong car preference and Class 4 including those with a moderate preference for cars and a strong lack of bike enjoyment. As in the linear version of the model presented in the previous section, the risk-cautious/pro-cyclist group seems to see the biggest benefit from protected infrastructure, signaled by the large coefficient for "agree", particularly for one-way protected bike lanes.

Table 5-9 Latent-Class Multinomial Logit Model for Perceived Comfort with Infrastructure Characteristics as Predictors and Individual Characteristics as Covariates (Outcome Model)

		Class 1	Class 2	Class 3	Class 4	Overall		
R^2 Value[#]		0.194	0.290	0.304	0.161	0.512		
Class Share		0.445	0.257	0.213	0.085	1.000		
	Response	Coefficients					P[##]	P[##](=)
Intercept	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.49	-0.64	-2.08	1.58			
	Agree	0.75	-0.28	-1.84	-0.81			
Bicycle Facility Types								
Bike Lane (BL)	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.65	1.89	0.21	1.55			
	Agree	1.99	1.92	-0.89	1.41			
Buffered BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.65	2.56	1.67	7.52			
	Agree	3.67	3.99	0.20	7.15			
One-way Protected BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.22	2.75	2.96	2.94			
	Agree	4.60	6.37	3.71	4.79			
Two-way Protected BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.99	2.03	2.08	2.65			
	Agree	2.42	4.78	3.18	4.27			
Multi-use Path	Disagree	0	0	0	0	***	<0.001	0.009
	Neutral	0.11	1.47	2.00	1.09			
	Agree	2.14	3.20	3.59	3.26			
Roadway Characteristics								
Parking	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.05	-0.09	-0.87	0.14			
	Agree	-0.26	-1.40	-0.39	-0.81			
Four Lanes	Disagree	0	0	0	0	**	0.004	0.510
	Neutral	-0.30	0.26	0.001	-0.25			
	Agree	-0.44	-0.22	-0.39	-0.93			
Framing Effects								
Buffered BL, No Parking	Disagree	0	0	0	0	***	<0.001	0.036
	Neutral	-0.42	1.09	0.37	0.78			
	Agree	0.42	1.70	2.44	0.33			
BL, No Parking	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-5.54	0.91	1.16	6.52			
	Agree	1.53	1.27	3.16	6.99			
BL, Two Lanes	Disagree	0	0	0	0	***	<0.001	--[###]
	Neutral	0.85	0.85	0.85	0.85			
	Agree	0.61	0.61	0.61	0.61			

Table 5-10 Latent-Class Multinomial Logit Model for Perceived Comfort with Infrastructure Characteristics as Predictors and Individual Characteristics as Covariates Continued (Class Membership Model and Means)

	Coefficients						Class Mean			
	Class 1	Class 2	Class 3	Class 4		P	Class 1	Class 2	Class 3	Class 4
Intercept	0	-0.26	-0.57	-1.24	***	<0.001	--	--	--	--
Bike Enjoyment	0	-0.16	-0.51	-0.53	***	<0.001	0.49	0.23	-0.30	-0.42
Risk Tolerance	0	-0.14	-0.16	-0.12	**	0.004	0.29	-0.03	-0.19	-0.19
Car Preference	0	-0.10	0.22	0.057	***	<0.001	-0.08	-0.15	0.33	0.19
Anti-exercise	0	0.12	0.24	0.14	***	<0.001	-0.27	-0.08	0.21	0.09
Current Cyclist	0	-0.26	-0.35	-1.22	***	<0.001	0.48	0.37	0.23	0.12
Log-Likelihood (Equally Likely Model)				-14038						
Log-Likelihood (Market Share Model)				-11936						
Log-Likelihood (Full Model)				-9063						
McFadden ρ^2				0.354						
Adjusted McFadden ρ^2				0.347						

*Significant at 0.050

**Significant at 0.010

***Significant at 0.001

#R^2 for latent class nominal regression in LatentGOLD is calculated as $R^2 = 1 - \frac{Error(model)}{Error(baseline)}$, where Error(model) is defined as the average of the sum of the squared differences between the observed choice probability (1 for the chosen option, 0 for all other options) and the posterior-probability weighted expected probability and Error(baseline) is the average of the sum of the squared differences between the observed choice probability and the predictions in the intercept only model

##P refers to the P-value for the Wald test of significance of the average effect across all classes

##P (=) refers to the P-value for a test of equality of coefficients across all three classes

###Constrained to be equal since initial model estimations indicated no significant differences across classes

The multinomial logit latent class model estimated for perceived safety is presented in Table 5-11 and Table 5-12. In this model, Class 1 consists of those who are pro-bike but risk-cautious. Class 2 is composed of risk-embracing bicycling enjoyers. Those in Class 3 are those with a preference towards car, while Class 4 is made up of those who are somewhat pro-car, anti-bike, and anti-exercise.

The coefficients for "agree" for Class 1 are large for each facility type, with that of one-way protected bike lanes being extraordinarily high. This further confirms the notion that for this subset of the population who enjoys biking but is more risk-cautious, the presence of quality protected facilities is fundamental to perceptions of bikeability. Furthermore, this segment of the population appears to enjoy biking just as much as their more confident counterpart in Class 2, indicating that the perception of risk and unsafety may be the only thing keeping those in described by Class 1 from biking at the same rates as the confident and enthused bicyclists.

Table 5-11 Latent Class Multinomial Logit Model for Perceived Safety with Infrastructure Characteristics as Predictors and Individual Characteristics as Covariates (Outcome Model)

		Class 1	Class 2	Class 3	Class 4	Overall		
R^2 Value		0.389	0.188	0.362	0.168	0.516		
Class Share		0.350	0.309	0.256	0.085	1.000		
	Response	Coefficients					P[##]	P[##](=)
Intercept	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.63	-1.20	-2.57	1.14			
	Agree	-1.40	0.48	-1.96	-0.37			
Bicycle Facility Types								
Bike Lane (BL)	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	1.72	0.56	0.45	1.12			
	Agree	2.71	2.11	-0.46	0.14			
Buffered BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	3.12	0.01	1.93	2.27			
	Agree	5.64	3.21	0.42	-0.23			
One-way Protected BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	8.05	-0.14	3.29	1.68			
	Agree	13.77	4.88	4.40	3.39			
Two-way Protected BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	1.81	0.55	2.78	3.36			
	Agree	6.64	2.12	3.95	4.37			
Multi-use Path	Disagree	0	0	0	0	***	<0.001	0.009
	Neutral	0.81	1.54	2.64	0.86			
	Agree	4.17	2.39	3.90	2.51			
Roadway Characteristics								
Parking	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.32	0.15	-0.83	-0.38			
	Agree	-1.92	-0.25	-0.54	-0.85			
Four Lanes	Disagree	0	0	0	0	**	0.009	0.120
	Neutral	-0.44	0.24	0.12	0.11			
	Agree	-0.14	-0.33	-0.51	0.004			
Framing Effects								
Buffered BL, No Parking	Disagree	0	0	0	0	***	<0.001	0.036
	Neutral	-5.05	1.45	0.75	5.96			
	Agree	1.68	1.05	2.41	8.10			
BL, No Parking	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	1.51	1.56	1.39	4.85			
	Agree	1.91	1.96	2.59	5.89			
BL, Two Lanes	Disagree	0	0	0	0	***	<0.001	--[###]
	Neutral	0.21	-5.30	-6.19	1.17			
	Agree	0.31	1.33	-0.63	1.88			

Table 5-12 Latent Class Multinomial Logit Model for Perceived Safety with Infrastructure Characteristics as Predictors and Individual Characteristics as Covariates Continued (Class Membership Model and Means)

	Coefficients						Class Mean			
	Class 1	Class 2	Class 3	Class 4		P	Class 1	Class 2	Class 3	Class 4
Intercept	0	-0.12	-0.26	-1.40	***	<0.001	--	--	--	--
Bike Enjoyment	0	0.001	-0.36	-0.49	***	<0.001	0.37	0.38	-0.14	-0.35
Risk Tolerance	0	0.12	-0.019	-0.051	**	0.014	0.06	0.27	-0.10	-0.22
Car Preference	0	0.063	0.20	0.14	**	0.013	-0.14	-0.045	0.21	0.15
Anti-exercise	0	0.072	0.23	0.30	***	<0.001	-0.27	-0.18	0.13	0.28
Log-Likelihood (Equally Likely Model)				-14021						
Log-Likelihood (Market Share Model)				-12557						
Log-Likelihood (Full Model)				-8610						
McFadden ρ^2				0.386						
Adjusted McFadden ρ^2				0.379						

*Significant at 0.050
**Significant at 0.010
***Significant at 0.001
#R^2 for latent class nominal regression in LatentGOLD is calculated as $R^2 = 1 - \frac{Error(model)}{Error(baseline)}$, where Error(model) is defined as the average of the sum of the squared differences between the observed choice probability (1 for the chosen option, 0 for all other options) and the posterior-probability weighted expected probability and Error(baseline) is the average of the sum of the squared differences between the observed choice probability and the predictions in the intercept only model
##P refers to the P-value for the Wald test of significance of the average effect across all classes
##P (=) refers to the P-value for a test of equality of coefficients across all three classes
###Constrained to be equal since initial model estimations indicated no significant differences across classes

Lastly, a latent class multinomial logit model was estimated for willingness to try bicycling, presented in Table 5-13 and Table 5-14**Error! Reference source not found.**. Since the "agree" and "strongly agree" categories have been collapsed in this model, the 9.6% of respondents who responded "strongly agree" to all options have been combined with the "agree" responses. Class 1 includes most of these cases, where most of the responses were "agree". Respondents in this class are characterized by a strong bicycle enjoyment factor along with risk tolerance. Class 2 comprises those with a moderate bike enjoyment and car preference but low risk tolerance. Class 3 contains those that are strongly anti-bike and that strongly prefer cars. Class 4 represents those with a moderate car preference and moderate dislike of bicycling. The coefficients of one-way protected bike lanes for the "agree" option for Classes 2 and 4 are rather large. For Class 2, this is indicative that those who would like to bike but may be concerned about the risk react much more positively to this type of facility than for other facilities. For Class 4, this indicates that those who have only a weak affinity to any particular mode, while not willing to try very many facilities, are rather willing to try bicycling on protected bike lanes.

Table 5-13 Latent Class Multinomial Logit Models for Willingness to Try Bicycling with Infrastructure Characteristics as Predictors and Individual Characteristics as Covariates (Outcome Model)

		Class 1	Class 2	Class 3	Class 4	Overall		
R^2 Value[#]		0.108	0.281	0.248	0.165	0.576		
Class Share		0.502	0.274	0.124	0.101	1.000		
	Response	Coefficients					P[##]	P[##](=)
Intercept	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.11	-0.94	-3.52	0.86			
	Agree	2.33	-0.05	-3.72	-1.36			
Bicycle Facility Types								
Bike Lane (BL)	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	2.16	0.96	-1.31	1.35			
	Agree	3.17	0.99	-0.54	0.35			
Buffered BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	2.30	1.28	-0.09	2.81			
	Agree	4.64	1.90	-4.48	3.08			
One-way Protected BL	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-0.40	2.46	1.86	8.34			
	Agree	4.04	5.53	2.74	10.57			
Two-way Protected BL	Disagree	0	0	0	0	***	<0.001	0.260
	Neutral	0.20	1.74	1.64	1.83			
	Agree	2.59	4.02	3.01	3.20			
Multi-use Path	Disagree	0	0	0	0	***	<0.001	0.020
	Neutral	0.49	1.04	2.58	1.24			
	Agree	2.33	2.53	3.99	3.83			
Roadway Characteristics								
Parking	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	0.17	-1.14	0.90	0.10			
	Agree	-0.46	-1.85	-1.20	0.55			
Four Lanes	Disagree	0	0	0	0	**	0.002	0.810
	Neutral	-0.35	0.00	-0.19	-0.36			
	Agree	-0.81	-0.44	-0.39	-0.57			
Framing Effects								
Buffered BL, No Parking	Disagree	0	0	0	0	***	<0.001	0.036
	Neutral	-6.73	0.52	1.97	5.78			
	Agree	0.10	1.49	4.29	6.52			
BL, No Parking	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-8.11	0.52	2.11	1.71			
	Agree	0.23	1.31	0.41	3.48			
BL, Two Lanes	Disagree	0	0	0	0	***	<0.001	<0.001
	Neutral	-1.01	-0.70	-6.58	7.34			
	Agree	-0.19	0.17	-3.50	8.00			

Table 5-14 Latent Class Multinomial Logit Models for Willingness to Try Bicycling with Infrastructure Characteristics as Predictors and Individual Characteristics as Covariates Continued (Class Membership Model and Means)

	Coefficients						Class Mean			
	Class 1	Class 2	Class 3	Class 4		P	Class 1	Class 2	Class 3	Class 4
Intercept	0	0.75	0.39	-0.64		0.270	--	--	--	--
Bike Enjoyment	0	-0.38	-1.20	-0.66	***	<0.001	0.65	0.12	-1.04	-0.33
Risk Tolerance	0	-0.10	-0.21	-0.08	*	0.029	0.33	-0.06	-0.52	-0.16
Car Preference	0	0.33	0.61	0.26	***	<0.001	-0.35	0.29	0.58	0.23
Anti-exercise	0	0.36	0.27	0.33	***	<0.001	-0.44	0.17	0.15	0.24
Caucasian/White	0	-0.53	-0.60	-0.76	***	<0.001	0.78	0.60	0.62	0.55
Age	0	0.008	0.020	0.028	***	<0.001	44	48	54	54
Female	0	0.70	0.45	0.36	***	<0.001	0.45	0.64	0.58	0.56
Bike Frequency	0	-0.41	-0.88	-0.04	***	<0.001	2.27	1.34	1.05	1.25
Bike Confidence	0	-0.23	-0.48	-0.40	**	0.001	3.60	3.22	2.79	2.99
Current Cyclist	0	-0.15	-0.51	-1.59	**	0.004	0.59	0.26	0.07	0.08
Log-Likelihood (Equally Likely Model)				-13306						
Log-Likelihood (Market Share Model)				-10566						
Log-Likelihood (Full Model)				-6698						
McFadden ρ^2				0.497						
Adjusted McFadden ρ^2				0.488						

*Significant at 0.050
**Significant at 0.010
***Significant at 0.001
#R^2 for latent class nominal regression in LatentGOLD is calculated as $R^2 = 1 - \frac{Error(model)}{Error(baseline)}$, where Error(model) is defined as the average of the sum of the squared differences between the observed choice probability (1 for the chosen option, 0 for all other options) and the posterior-probability weighted expected probability and Error(baseline) is the average of the sum of the squared differences between the observed choice probability and the predictions in the intercept only model
##P refers to the P-value for the Wald test of significance of the average effect across all classes
##P (=) refers to the P-value for a test of equality of coefficients across all three classes

The multinomial logit models presented serve as a supplement to the previously presented regression models by providing a robustness check for the primary models in light of the theoretical limitations of the linear regression models presented therein. Despite some variations, results from these models are quite congruent to those presented in the previous section, leading to the ultimate decision to focus primarily on the linear models for greater ease of interpretability and parsimony.

5.2.4 Discussion

The four types of cyclists (Geller 2006; Dill and McNeil 2013) have been widely accepted as a useful typology for explaining differences in preferences for bicycle facilities. However, this typology combines both interest level (strong, enthused, interested, no way) and comfort level (fearless, confident, concerned, no how) in a sort of double-barreled manner. An advantage of the latent-class models is that bike-enthusiasm and risk-tolerance are measured independently, allowing the identification of an otherwise hidden subset of the population who have high levels of bike enjoyment but may be more cautious.

The best example of this is the latent class regression model for perceived safety in Table 5. In this model, the class that would be considered closest to the "interested but concerned" type (Class 2) actually has a similar, if not somewhat higher, average bike enjoyment score than the class closest to the "enthused and confident" type (Class 3). For this sample, it seems a better classification for these two groups would be the "enthused but cautious" and "enthused and confident". The implications of this discovery are that differences in perceptions of the safety and comfort of bicycle facilities can be even more closely linked to attitudes regarding risk than to biking interest. Compared to the distribution of the different types of cyclists from the typology of Geller (2006), our analogous classes have noticeably different percentages. Our risk-embracing group (24% in the perceived comfort model and 16% in the perceived safety model) would roughly correspond to Geller's "strong and fearless" and "enthused and confident" groups (together estimated at 8% of the population), while our risk-cautious group (26% in the perceived comfort model and 32% in the perceived safety model) would correspond to Geller's "interested but concerned" group (estimated at 60% of the population), though the two groups in this study appear to be much closer in size than Geller (2006) suggests.

Patterns for the impact of facilities on different groups are less clear for willingness to try. Whereas perceptions of the relative comfort and safety of bicycle facilities partially varied along lines of risk-tolerance that were independent of affinity toward bicycling, classes were split, with respect to willingness to try, along a more one-dimensional spectrum of pro-bike and non-pro-bike. Respondents in the most pro-bike segment of the model in Table 6 "strongly agreed" that bicycling on such a facility would be something they would try, no matter which facility was shown to them, while the other two segments' reactions to infrastructure types scaled down along with their bike enjoyment score. This trend may be an indication that respondents' expression of willingness to try bicycling on particular roadways largely depends on their own views of cycling or perhaps an intrinsic willingness to cycle in general, and that the effects of the facilities are less relevant for those who already have a strong willingness to cycle in general.

5.3 Chapter Summary

The purpose of the research presented in this chapter is to explore differences in preferences and perceptions of bicycle facilities between various groups. The approach taken here is novel in its application of latent class models to parse taste variations in perceptions of bicycle facilities. The data for this study come from surveys (N=2,157) deployed in 10 communities as part of two related studies. Key outcome variables include responses to a series of hypothetical roadways with various roadway characteristics and bicycle facility types, where respondents were prompted to rate bicycling on each roadway in terms of perceived comfort, perceived safety, and something they would try. Each of the variables of interest was modeled using linear regression both for the pooled sample and for latent class segmentation. Explanatory variables consisted of dummy variables for roadway characteristics (number of vehicular lanes and presence/absence of on-street parking) and bicycle facility types. Attitudinal factors were developed using exploratory factor analysis on a set of attitudinal items. The attitudinal factors, along with sociodemographic characteristics, were also included as explanatory variables in the linear models and as class-membership covariates in the latent class models.

Results from the models confirm that people in general view separated and protected bicycle facilities as more favorable. Those with pro-bike attitudes and greater risk-tolerance also had higher ratings of facilities, while those with preferences towards cars and those who are more anti-exercise had lower ratings of facilities.

The primary novel finding from this chapter comes from implementation of latent class models. These models allowed the impact of each explanatory variable to vary among different classes. For the perceived comfort and perceived safety latent class models, as opposed to just the expected “pro-bike” and “pro-car” classes, a “pro-bike/risk-cautious” class was also discovered. While all classes showed improved perceptions of comfort and safety for more separated facilities, this class showed the most sensitivity to separated facilities.

The implications of this finding are that there likely exists a substantial portion of the general population that enjoys bicycling but is simply deterred from seriously considering adopting it as a transportation mode due to the risks. The sensitivity this segment shows to protected facilities indicates that perceptions of bikeability can be drastically improved through high-quality protected bike facility projects. Whereas other typologies of bicyclists have intertwined both interest in bicycling and tolerance of its risks, separating these two constructs and setting design standards for those who are more risk-averse (i.e. protected bike lanes), rather than those who are less interested in bicycling, could reasonably lead to a greater adoption of bicycling.

CHAPTER 6. THE EFFECTS OF INFRASTRUCTURE PROJECTS ON PERCEPTIONS OF IMPROVED BIKABILITY

The analyses presented so far in this dissertation have only been conducted on data from the first-wave survey without distinguishing between control and treatment communities. The focus of this chapter is on responses to the second-wave survey, which was deployed after the implementation of the bicycle infrastructure projects of interest. The objective is to identify differences between those in the treatment and control groups, particularly in regard to their perceptions of how the bikability of their neighborhood had changed over the course of the previous one to two years.

Since second-wave survey invitations were sent out by mail to the addresses of all who had responded to the first wave, with no way of ensuring that the same household member completed both surveys, it was inevitable that some follow-up surveys would be completed by a different respondent than for the first invitation. Accordingly, pairs of respondents with non-matching demographics (race/ethnicity, gender, and age) were excluded from their respective datasets. The first section of this chapter includes analysis on changes in bicycling frequency using excerpts from the NCHRP and GDOT reports, with further analysis on perceptions of improvements in bikability coming from a joint analysis of the combined dataset.

6.1 Changes in Bicycling Frequency

One of the primary questions at the outset of this research was regarding the effectiveness of bicycling facilities for trip-making. In each wave of the survey, respondents were asked to report their frequency of making trips using certain modes, both for commute purposes and other purposes. Analysis of each of the treatment communities was attempted, though the number of bicyclists in both the before and after surveys was prohibitively small for making statistical determinations.

In the respective reports for the two major funding sources, Georgia Department of Transportation (Watkins et al. 2019) and National Cooperative Highway Research Project 08-102 (publication forthcoming), respondents were divided into groups based on their bike trip frequency in wave 1, and the number in each group was tabulated based on how many decreased, increased, or made no change in bicycling frequency. The following tables are excerpts from the respective reports. Table 6-1 and Table 6-2 show cross-tabulations for each group within each neighborhood and the number of those in each group who decreased, increased, or did not change in frequency for commute trips and other trips, respectively.

Table 6-1 Changes in Bike Commuting Frequency from First to Second Wave for Atlanta Communities (Source: Watkins et al. 2019)

First Wave Frequency	Eastside			Grant Park		
	Decreased	No change	Increased	Decreased	No change	Increased
Never	NA	94	12	NA	106	10
<1 day a month	4	1	0	2	3	4
1–3 days a month	5	1	1	1	4	1
1–2 days a week	5	3	0	1	4	1
3–4 days a week	7	3	0	4	2	2
≥5 days a week	0	4	NA	0	3	NA
Total	21	106	13	8	122	18

First Wave Frequency	Westside			South Atlanta		
	Decreased	No change	Increased	Decreased	No change	Increased
Never	NA	20	2	NA	42	1
<1 day a month	2	2	0	3	0	0
1–3 days a month	1	1	1	1	1	0
1–2 days a week	0	0	0	0	0	0
3–4 days a week	0	0	1	0	0	0
≥5 days a week	1	0	NA	0	0	NA
Total	4	23	4	4	43	1

*Note: Eastside and Westside were treatments, Grant Park and South Atlanta were controls

Table 6-2 Changes in Frequency of Other Trips by Bike from First to Second Wave for Atlanta Communities (Source: Watkins et al. 2019)

First Wave Frequency	Eastside			Grant Park		
	Decreased	No change	Increased	Decreased	No change	Increased
Never	NA	71	17	NA	87	22
<1 day a month	7	16	10	13	15	9
1–3 days a month	10	15	12	13	10	5
1–2 days a week	16	10	2	7	12	2
3–4 days a week	2	4	0	5	2	2
≥5 days a week	4	3	NA	4	0	NA
Total	39	119	41	42	126	40

First Wave Frequency	Westside			South Atlanta		
	Decreased	No change	Increased	Decreased	No change	Increased
Never	NA	47	9	NA	60	10
<1 day a month	1	3	1	5	2	1
1–3 days a month	2	3	1	3	1	1
1–2 days a week	1	1	0	0	0	1
3–4 days a week	1	0	1	2	0	0
≥5 days a week	0	0	NA	0	0	NA
Total	5	54	12	10	63	13

*Note: Eastside and Westside were treatments, Grant Park and South Atlanta were controls

Table 6-3 and Table 6-4 report the combined tabulation for the remaining six communities, with Chattanooga, Opelika, and Anniston being the treatments and Birmingham, Northport, and Talladega being the controls.

Table 6-3 Numbers of Respondents Increasing, Decreasing, or not Changing Bike Commute Frequency between Wave 1 and Wave 2 (from NCHRP 08-102, final report forthcoming)

First Wave Bike *Commute* Frequency	Treatments (N=70)			Controls (N=85)		
	Decreased	No change	Increased	Decreased	No change	Increased
Never	NA	58	5	NA	69	6
<1 day a month	1	0	1	3	3	0
1–3 days a month	0	1	0	3	0	0
1–2 days a week	0	1	0	1	0	0
3–4 days a week	2	0	1	0	0	0
≥5 days a week	0	0	NA	0	0	NA
Total	3	60	7	7	72	6

Table 6-4 Numbers of Respondents Increasing, Decreasing, or not Changing Bike Other Trip Frequency between Wave 1 and Wave 2 (from NCHRP 08-102, final report forthcoming)

First Wave Bike *Other Trip* Frequency	Treatments (N=181)			Controls (N=181)		
	Decreased	No change	Increased	Decreased	No change	Increased
Never	NA	142	8	NA	138	11
<1 day a month	8	5	4	8	7	2
1–3 days a month	1	4	0	2	3	1
1–2 days a week	1	2	2	4	1	0
3–4 days a week	0	1	0	3	1	0
≥5 days a week	3	0	NA	0	0	NA
Total	13	154	14	17	150	14

While the ultimate goal of these studies was to quantify bicycle trip-making changes accompanying bicycle facility treatments, the small number of bicyclists makes this question unanswerable with any degree of thoroughness. However, anecdotal observations indicate that in the Atlanta treatment neighborhoods, a small number of residents increased biking for non-commute trips for the Eastside Extensions (from 39 to

42) and the Westside BeltLine (from 5 to 12). Despite the lack of clear evidence on travel *behavior*, *perceptions of the facilities* in question and how respondents may have changed perceptions of their respective communities are also valuable measures, and do not suffer from small sample sizes. In the remainder of this chapter, these two sets of measures are combined and analyzed in greater detail.

6.2 Description of Combined Analyses

For the remainder of this chapter, the GDOT and NCHRP datasets were combined for joint analysis. The matching of respondents between the first and second waves was reassessed to provide a more stringent set of criteria by including the number of years spent living in the home. This resulted in a dataset of 855 respondents. The distribution of respondents in the combined sample is presented in Table 6-5.

Table 6-5 Distribution of Respondents between Study Areas (N=855)

Treatment Site	Respondents	Control Site	Respondents
Anniston	58	Talladega	28
Opelika	70	Northport	100
Chattanooga	52	Birmingham	63
Westside	62	South Atlanta	75
Eastside	167	Grant Park	180
TOTAL Treatment	409	TOTAL Control	446

6.2.1 Perceptions of Improvement in Bikability

One of the new questions added to the second-wave survey prompted respondents to consider how transportation in their community had changed since the time of the first survey (either Fall 2016 or Spring 2017). They were presented with the prompt “We would like to know whether transportation in your community has changed since [date of first survey], either for better or worse. Please give your opinion for each category below.” They were asked to rate each item on a 5-point Likert-type scale with the options of “Much worse,” “Somewhat worse,” “Neutral/ No change,” “Somewhat better,” and “Much better”. Respondents were presented with sub-items for various aspects of several modes:

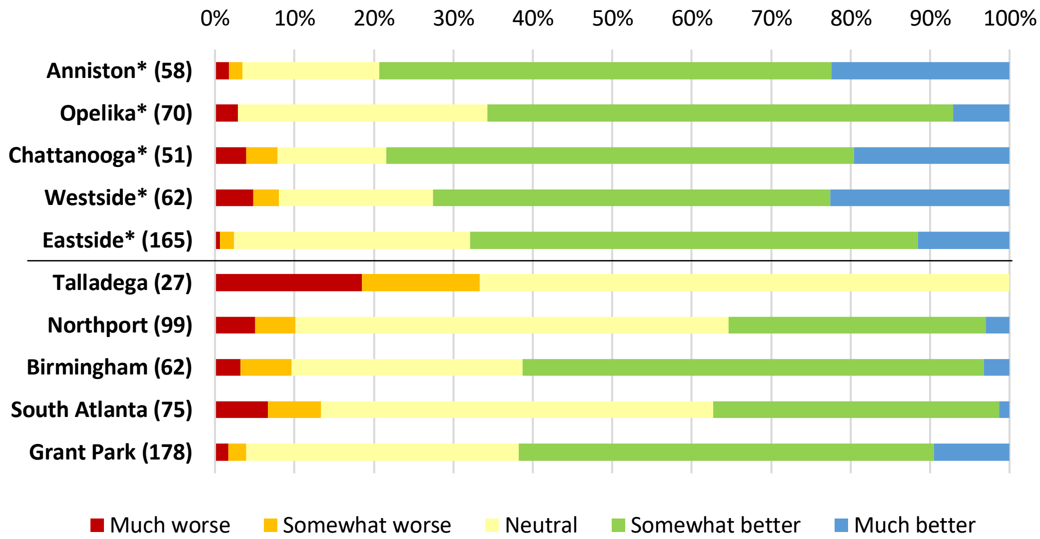
- “Traffic congestion,”
- “Parking availability,”

- "Public transit route coverage (can reach more/fewer places),"
- "Public transit frequency (comes more/less often),"
- "Sidewalk availability (more/fewer of them),"
- "Sidewalk quality,"
- "Availability of taxi/ Uber/ Lyft,"
- "Bicycle safety,"
- "Availability of bicycle lanes and trails," and
- "Quality of bicycle lanes and trails."

Analyses in this chapter focus on the final three, bike-related, items. For analysis of reactions to the full spectrum of transportation system changes, please see the NCHRP and GDOT reports. Responses for each of these bicycle-related system changes were tabulated by neighborhood. The distribution of responses for perceived changes in availability of bicycle lanes and trails is presented in Figure 6-1. Most respondents in the treatment neighborhoods reported improvements, while respondents in control neighborhoods responded as neutral or that there had been no change. The main exception to this is Grant Park, which served as the control neighborhood to the Eastside BeltLine Extension and was the neighboring community. It is likely that the positive responses in Grant Park could be representative of a spillover effect from the neighboring treatment community.

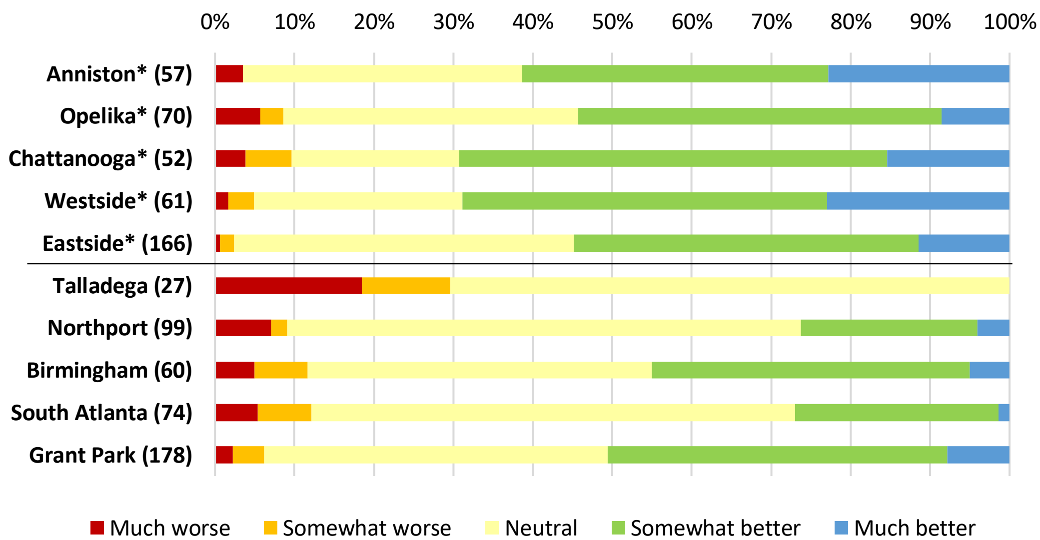
Responses for perceived changes in quality of bicycle lanes and trails are shown in Figure 6-2. These responses follow a similar trend as that of availability, though with a slightly smaller portion (albeit still a majority) of those in the treatment group responding positively. Interestingly enough, even though the treatment in Anniston was only a sharrow—something not often considered high-quality—the portion of those reporting improvement was still similar to those in other treatment communities.

The distribution of responses for perceived changes of bicycle safety is presented in Figure 6-3. The portion of those in treatment groups reporting improvements in this item is more modest than for the previous two items, though is still greater than those reporting worse conditions. The relationship between perceived bike safety and the treatment may thus be a somewhat dampened version of the apparent relationship between more direct measures of bicycling facilities and the treatment, indicating that there is more to perceived bike safety than simply perceptions of improved facility quality and availability.



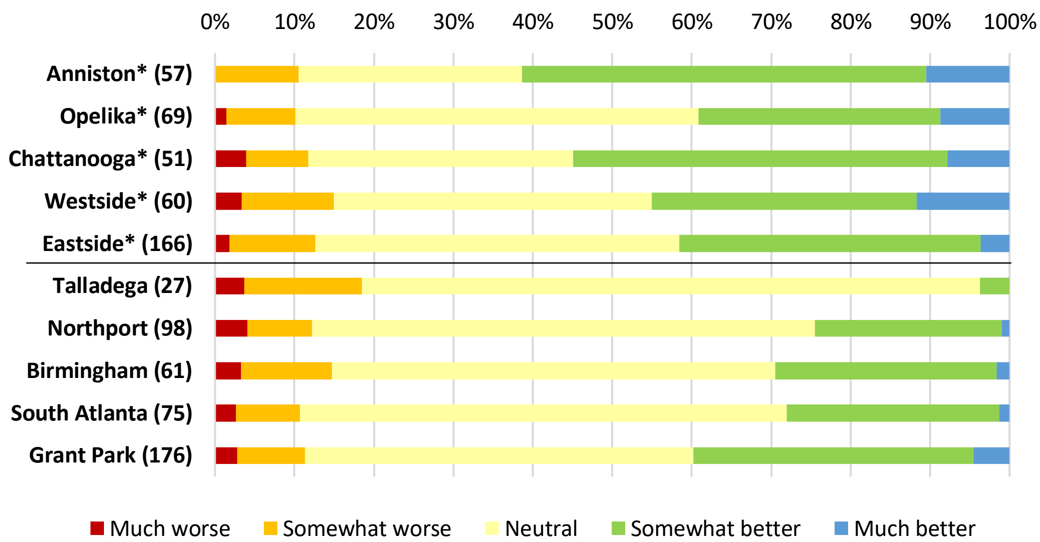
*Treatment Neighborhood
(Number of responses)

Figure 6-1 Responses for Perceived Changes in Availability of Bicycle Lanes and Trails



*Treatment Neighborhood
(Number of responses)

Figure 6-2 Responses for Perceived Changes in Quality of Bicycle Lanes and Trails



*Treatment Neighborhood
(Number of responses)

Figure 6-3 Responses for Perceived Changes in Bicycle Safety

6.2.2 Attitudes

Given the major role of attitudes in shaping perceptions and preferences for bicycling facilities outlined in the previous chapters, the consistency of these factors between the first and second waves is investigated. The attitudinal factors used in this dissertation were described in the partial pattern loading matrix in Table 3-3 of Chapter 3. Table 6-6 presents the average scores on each factor for each wave of the survey, along with the t-statistic and associated P-value for testing the equality of mean factor scores across waves. Although small variations exist for each of these factors, the differences were not significant for most of the attitudes. The only attitudes that were significantly different (at the 5% level) were car preference and multimodality, both of which decreased. In isolation, either of these changes could be cause for concern, but taken together, the two changes seem to have contradictory implications, as a decrease in car preference could signify an overall increase in the usage of other modes while a decrease in multimodal attitudes would likely signify an increase in car preference. However, both changes are rather small (0.07 standard deviations), and the one for multimodal is only of borderline significance. On average, the other five attitudes of interest did not drastically change over the course of the study. In particular, the consistency of bike enjoyment and risk tolerance between waves is interesting. These particular attitudes were instrumental in the previous analyses in Chapter 5 in explaining taste heterogeneity for perceptions of comfort and safety of bicycling facilities. Since these attitudes, along with the other measured attitudes, did not change from wave 1 to wave 2, it is conceivable that perceptions of changes in the quality and availability of bicycling facilities in the second wave would be more a function of the actual built environment changes in the community than of attitudinal changes at the individual level. Moreover, the relative consistency of these attitudes improves their ability to be used to explain other changes through time.

Table 6-6 Paired T-test for Equality of Mean Attitudinal Factor Scores between Wave 1 and Wave 2

	Wave 1 Average (N=855)	Wave 2 Average (N=855)	T Statistic	P
Car Preference	-0.0055	-0.079	-2.62	0.009
Bike Enjoyment	-0.0068	0.0086	0.48	0.630
Risk Tolerance	-0.032	-0.054	-0.52	0.606
Anti-exercise	-0.061	-0.088	-0.72	0.469
Utilitarian Travel	-0.045	-0.11	-1.93	0.054
Multimodal	0.061	-0.011	-1.98	0.048
Cycling Rarity	0.023	0.073	0.94	0.345

6.3 Regression Models

The observations of section 6.2 based on response distribution highlight some major themes that warrant additional analysis. Specifically, we want to investigate the variables associated with each of the three perceptions of improvement: facility availability, facility quality, and safety. The first set of analyses is conducted using linear regression models, while ordered logit models are used in the next subsection. The linear regression models for each of the three perceptions of improvement are presented in Table 6-7.

The explanatory variables consist of several dummy variables for neighborhood level characteristics such as whether it is an urban neighborhood (Birmingham, Chattanooga, or Atlanta) as opposed to a rural / small-town neighborhood (Anniston, Opelika, Talladega, or Northport), and if the neighborhood received an off-street facility treatment (Atlanta: Eastside and Westside) or on-street facility treatment (Chattanooga, Opelika, or Anniston) as opposed to no treatment (South Atlanta, Grant Park, Birmingham, Northport, or Talladega). The urban coefficient was significant and positive in the availability and quality models, indicating that respondents in urban communities had a greater tendency to report improvement compared to those in rural / small-town communities. Both facility coefficients were significant in the availability and quality models, while only the on-street coefficient was significant in the safety model, though the two coefficients (along with the urban coefficient) for safety were all in the same direction as in the other two models but with smaller magnitudes. Interestingly, the positive impact on perceptions of improvement was greater for on-street facilities than for off-street facilities, which is somewhat counterintuitive given the preference for off-street facilities exhibited in previous chapters. This could be a result of a number of potential factors, such as a possible confounding of Atlanta-specific effects due to both off-street facilities being located in the metro area, where new bike infrastructure has been introduced on an ongoing basis over the past several years. Alternatively, it could be a representation of the "out of sight—out of mind" concept, that the average person is more likely to notice and remember an improvement when it is visible in the natural course of daily travel.

Table 6-7 Linear Regression Models for Perceptions of Improvement in Bicycle Facility Availability, Bicycle Facility Quality, and Bicycle Safety (1=Much worse, 5=Much better)

Variable	Availability			Quality			Safety		
	Coefficient		P	Coefficient		P	Coefficient		P
Constant	3.14	***	<0.001	3.16	***	<0.001	3.07	***	<0.001
Neighborhood Level Dummy Variables									
Urban	0.30	***	<0.001	0.17	*	0.029	0.08		0.252
Off-street Facility	0.27	***	<0.001	0.30	***	<0.001	0.079		0.247
On-street Facility	0.88	***	<0.001	0.73	***	<0.001	0.56	***	<0.001
Individual Level Variables									
(On-street Facility) x (Distance)	-0.43	*	0.027	-0.38		0.055	-0.30		0.116
Cyclist	0.12		0.097				0.24	***	<0.001
Anti-Exercise	-0.069	**	0.003	-0.088	**	0.001			
Utilitarian Travel	-0.047	*	0.042						
Multimodality				0.056	*	0.019			
Cycling Rarity				-0.074	***	<0.001	-0.043	*	0.015
# of Responses	847			844			840		
R^2	0.107			0.111			0.050		
Adj. R^2	0.100			0.103			0.043		

*Significant at P = 0.050 or better

**Significant at P = 0.010 or better

***Significant at P < 0.001

Several explanatory variables were defined on the individual level. The straight-line distance (in miles, capped at 1) to the treatment facility for those in treatment communities where there was an on-street facility treatment was significant and negative in both facility-based models, indicating that the perceived improvement for those in communities with on-street facility treatments tended to diminish for those farther away from the treatment itself. For example, the average respondent in an on-street facility treatment neighborhood would have roughly one full additional point on the 1-5 scale for perceptions of availability, though if that respondent resided a mile away from the nearest treatment the increases in perceptions were nearly halved. The dummy variable for cyclist was set to 1 for those who reported bicycling more than 1 mile per week in both the first and second waves and 0 for all others. The cyclist coefficient was significant and positive in both the facility availability model and the bike safety model, while it was insignificant in the facility quality model. This suggests that those who are at least occasional bicyclists tended to report somewhat greater improvements in facility quality and safety than did the study group in general. The remainder of the individual level variables come from the attitudinal factor analysis. Since these attitudes were fairly consistent between the two waves, only the second wave scores were used in the models. A negative relationship is observed between the anti-exercise attitude and all three dependent variables, indicating that those who do not view exercise as important tend to have less positive perceptions of each of the three measures of improvement. The negative coefficient of the utilitarian travel attitude in the facility availability model indicates that for those that view traveling in a more utilitarian manner (i.e. simply as a means to get to a destination), perceptions of improvement in bicycling facility availability were generally lower. Conversely, the positive coefficient for the multimodal attitude in the facility quality model suggests that those with an openness and desire to travel multimodally tended to have slightly elevated levels of perceptions of improvement in bicycle facility quality. The cycling rarity coefficient was negative in both the facility quality and bike safety models, indicating that those that feel that bicycling for transportation is a rare phenomenon seem to have lower perceptions of improvement. Collectively, these results provide interesting evidence of the way in which perceptions of the external world are filtered through internal predispositions.

6.4 Ordered Logit Models

Although Likert-type variables can be reasonably approximated by linear regression models when there are four or more categories (Bentler and Chou 1987), responses to these questions were overwhelmingly concentrated on only three responses – somewhat worse, neutral and somewhat better (as was shown previously in Figure 6-1, Figure 6-2, and Figure 6-3). As such, ordered logit models for each dependent variable were estimated, as shown in Table 6-8. Since few respondents chose either of the extreme responses, the variable was collapsed into the three categories.

The results of these ordinal models mirrors those of the linear models. Some of the main differences between the two model types are the lack of significance of two coefficients in the ordered logit facility quality model. The distance to on-street facilities coefficient maintains its negative sign, but the P-value jumped from 0.033 to 0.255. This lack of significance indicates that, while there still seems to be evidence that those who are farther away from their on-street treatments have lower positive perceptions of improvements in the quality of bicycling facilities in their community, this evidence is not nearly as strong as the linear models suggest. The other coefficient that is no longer significant when converted to ordinal models is the multimodal attitude. This coefficient also maintains its positive sign, but the P-value increases from 0.033 to 0.115. As the ordinal models are less susceptible to potential issues relating to the sparse representation of each extreme, interpretation of the coefficients that were significant in the linear models but not the ordinal models should be much more conservative.

Table 6-8 Ordered Logit Models for Perceptions of Improvement in Bicycle Facility Availability, Bicycle Facility Quality, and Bicycle Safety

Variable	Availability			Quality			Safety		
	Coefficient		P	Coefficient		P	Coefficient		P
Intercepts									
Worse | Neutral	-1.67	***	<0.001	-1.93	***	<0.001	-1.51	***	<0.001
Neutral | Better	0.76	***	<0.001	0.88	***	<0.001	1.04	***	<0.001
Neighborhood Level Dummy Variables									
Urban	0.79	***	<0.001	0.49	**	0.009	0.25		0.162
Off-street Facility	0.57	**	0.002	0.61	***	<0.001	0.15		0.360
On-street Facility	2.23	***	<0.001	1.56	***	<0.001	1.24	***	<0.001
Individual Level Variables									
(On-street Facility) x (Distance)	-0.89		0.117	-0.43		0.255	-0.53		0.266
Cyclist	0.38	*	0.044				0.68	***	<0.001
Anti-Exercise	-0.22	***	<0.001	-0.23	***	<0.001			
Utilitarian Travel	-0.11		0.057						
Multimodality				0.11		0.062			
Cycling Rarity				-0.15	***	<0.001	-0.10	*	0.027
# of Responses	847			844			840		
McFadden R^2	0.071			0.062			0.028		
Nagelkerke. R^2	0.141			0.127			0.061		

*Significant at P = 0.050 or better

**Significant at P = 0.010 or better

***Significant at P < 0.001

The parallel lines assumption for the ordinal models was tested using the Brant parallel line test, presented in Table 6-9. In this test, a large chi-square statistic for a particular variable would indicate that the impact of that explanatory variable has a varying effect on the outcome variable at different levels, which would violate the assumptions of ordered logit models. None of the test statistics are significant in any of the three models, which indicates that the proposed models sufficiently meet the parallel lines assumption and are appropriately within the assumptions of ordered logistic models.

Table 6-9 Brant Parallel Line Test Results for Ordered Logistic Regression Models for Perceptions of Improvement in Bicycle Facility Availability, Bicycle Facility Quality, and Bicycle Safety

Variable	Availability			Quality			Safety		
	χ^2	df	P	χ^2	df	P	χ^2	df	P
Combined Model	7.36	7	0.393	12.75	7	0.078	12.76	6	0.047
Neighborhood Level Variables									
Urban	2.28	1	0.131	3.33	1	0.068	2.03	1	0.154
Off-street Facility	0.01	1	0.797	1.35	1	0.246	2.94	1	0.086
On-street Facility	0.01	1	0.763	1.39	1	0.238	0.88	1	0.348
Individual Level Variables									
(On-street Facility) x (Distance)	0.84	1	0.357	0.01	1	0.931	0.24	1	0.625
Cyclist	0.17	1	0.677				0.05	1	0.820
Anti-Exercise	0.71	1	0.394	1.22	1	0.270			
Utilitarian Travel	1.24	1	0.266						
Multimodality				0.93	1	0.336			
Cycling Rarity				0.13	1	0.720	0.45	1	0.500

6.5 Chapter Summary

Study participants were invited to participate in two waves of the survey. In the second wave, they were asked about their perceptions of how bikability in their community has changed. Respondents in the treatment areas, where various bicycling facilities opened between the time of the first and second wave surveys, generally reported more positive perceptions of improvements in bicycling facility availability and quality, and, to a somewhat lesser extent, bicycling safety. In contrast, respondents in control areas, where no similar bicycling facilities opened during the study period, were (unsurprisingly) rather neutral with respect to perceived improvements. Talladega (the control for Anniston) was a notable exception, where responses were overwhelmingly negative, perhaps due to some characteristic specific to this town that is not captured by any of the measured variables. Another deviating control community was Grant Park in Atlanta (the control for the Eastside Extension neighborhood), where responses were surprisingly positive and similar to those of the Eastside. This is likely due to the proximity and interconnectedness of these two neighborhoods and the potentially extra far-reaching impact of the Eastside treatment.

Analysis of perceptions and attitudes during both waves revealed interesting patterns for perceptions of change. Firstly, attitudes, which were previously identified in Chapter 5 as major contributors to the perceptions of bicycling facilities, did not significantly change between the first and second wave, indicating that if such attitudes were to change with time, the short window of one to two years was not sufficient in this case. Therefore, in the interest of parsimony and avoiding collinearity, only the second wave attitudes were included.

Linear regression and ordinal logistic regression models were also estimated on responses to perceptions of improvement. Those in urban settings had more positive perceptions than their rural / small-town counterparts. Those in treatment areas with on-street facility treatments responded significantly more positively than those in control communities, though the apparent impact of the treatment on perceptions of improvement generally decreased for those farther away from the treatment itself.

The impacts of these findings are instructive in assessing the benefits of bicycling facility investments. Although actual changes in behavior can be difficult to measure and may take years to come to fruition, the way a potential bicyclist perceives his or her environment is more apparent in the near term. While on-street facilities are often considered lower quality than off-street facilities, the heightened visibility of these types of facilities can be instrumental in changing people's perceptions of biking in their neighborhood. Even the sharrow project included in this study was effective in producing perceptions of improvement in bicycling in the Anniston community, even though such facilities are not typically viewed as safe or preferable facilities. The research outlined in this chapter adds this as a major contribution: that facility improvements aimed at improving perceptions of bikability can be an effective tool to shape how potential bicyclists view the suitability of their environment.

CHAPTER 7. CONCLUSIONS

7.1 Contributions

Despite the field's heightened interest in bicycling research, much of the current work is carried out in places with existing bicycling networks and a culture of bicycling for transportation. The data obtained for the analyses in this thesis are the result of multiple large high-resolution data collection efforts. With more than 40,000 invitees, the goals of these data collection efforts were to overcome the major barriers of notoriously low response rates (6.2% in the first wave, then 51% retention in the second wave) for high-quality surveys and the relatively infrequent instances of bicycling for transportation. As explained below, the research presented in this dissertation used this survey data to develop three major contributions to the literature.

The first major contribution of the dissertation is outlined in Chapter 4. The models in this chapter revealed strong positive perceptions of comfort and safety connected to separated and protected bicycling facilities, along with a greater willingness to try bicycling on such facilities. User characteristics were significant in explaining respondents' perceptions of being comfortable, safe, and willing to try biking. Sociodemographic information was more influential in predicting willingness to try, indicating that even when safety and comfort are similarly perceived across population segments, willingness to try can differ. The key component of this contribution comes from the segmented models, which indicate that the influence of explanatory variables on perceptions of infrastructure characteristics can be substantially different among different rider types. Regular utilitarian cyclists overwhelmingly perceived separated facilities as safer than sharrows, with the relative impact of these facilities being even greater for this group than the rest of the sample. However, this group's perceptions of safety were less negatively associated with the presence of parking. Occasional/recreational cyclists' preferences were surprisingly similar to those of potential cyclists, with no significant difference for perceived comfort and safety, and only education and age having significantly different effects for willingness to try. Those who are not able to bike did not differ significantly from the base of potential cyclists except in the willingness to try model, though the reported differences indicate that these respondents should likely be excluded from models for willingness to try bicycling.

The second major contribution is discussed in Chapter 5. The approach taken here is novel in its application of latent class models to parse taste variations in the influence of explanatory variables on the perceptions of bicycle facilities. Attitudinal factors were developed using exploratory factor analysis on a set of attitudinal items, which were included as latent class membership covariates. The primary novel finding from this chapter comes from the latent class models, which allowed the impact of each explanatory variable to vary among different classes. For the perceived comfort and perceived safety latent class models, as opposed to just the expected "pro-bike" and "pro-car" classes commonly used in practice, a "pro-bike/risk-neutral" class was also discovered. While all classes showed improved perceptions of comfort and safety for more separated facilities, this class showed the most sensitivity to separated facilities. The implications of this finding are that there likely exists a substantial portion of the general population that enjoys bicycling but is simply deterred from seriously considering adopting it as a transportation mode due to the risks. The sensitivity this segment shows to protected facilities indicates that perceptions of bikeability can be drastically improved through high-quality protected bike facility projects. Whereas other typologies of bicyclists have intertwined both interest in bicycling and tolerance of its risks, separating these two constructs and setting design standards for those who are more risk-averse (i.e. protected bike lanes), rather than those who are less interested in bicycling, could reasonably lead to a greater adoption of bicycling.

The last major contribution of the dissertation and the research that supports it is in the ambitious attempt of a rigorous and multi-faceted quasi-experimental (before and after with controls) design, of which a part is detailed in Chapter 6. Due to the extended scope of such a study design, many studies compromise on the research design by taking a cross-sectional approach or severely limiting the number of study locations. A major part of this contribution comes from the struggle of trying to measure small changes in bicycling facility usage when bicycling is already a fringe-mode. Although usage is one of the ultimate metrics desired for assessing the value of a facility, it is not necessarily a reliable metric to be able to measure in the matter of one to two years, particularly in areas where bicycling is not widespread. In such cases, perceptions of the bikability of the environment may be better measures of the effectiveness of the facility treatments, which is likely a major step towards behavior change. Those in treatment areas with on-street facility treatments responded significantly more positively than those in control communities, though (not surprisingly) the apparent impact of the treatment on perceptions of improvement generally decreased for those farther away from the treatment itself. While on-street facilities are often considered lower quality facilities than off-street facilities, the heightened visibility of these types of facilities can be instrumental in changing people's perceptions of biking in their neighborhood. Even the sharrow project included in this study was effective in producing perceptions of improvement in bicycling in the Anniston community, even though such facilities are not typically viewed as safe or preferable facilities. The facility improvements aimed at improving perceptions of bikability can be an effective tool to shape how potential bicyclists view the suitability of their environment.

In summary, the research described in this dissertation was intended to answer several questions. The questions are repeated as follows (with subsequent sections outlining how the dissertation answers these questions):

- What are the relative preferences of current and potential bicycle users for different types of bicycle facilities?
- How do such preferences vary by demographic and attitudinal characteristics?
- What role do bicycle facilities play in perceptions of improved bikeability and changes in travel behavior?

7.1.1 What are the relative preferences of current and potential bicycle users?

The analysis in Chapter 4 assessed preferences for different types of bicycle facilities by using stated responses to images of hypothetical bicycling facilities. This analysis confirmed the hypothesis that, even in areas where bicycling for transportation is not widely accepted, facilities that give more separation between bicyclists and motorists were preferred. Furthermore, segmenting respondents based on their current bicycling behavior (potential cyclists, recreational cyclists, regular/utilitarian cyclists, and those unable to cycle) highlighted differences in preferences. Some of the most notable differences were in perceptions of safety for regular utilitarian cyclists, who generally saw bike lanes, buffered bike lanes, and protected bike lanes as more of a bonus for safety (as compared to sharrows) then the rest of the sample. Other notable findings were that, despite age and access to a vehicle being generally associated with lower reported willingness to try bicycling, these characteristics had a more neutral association with willingness to try bicycling for those who were already regular utilitarian bicyclists and for those unable to bike.

7.1.2 How do preferences vary by demographic and attitudinal characteristics?

The models presented in Chapter 5 shed light on how demographics, and more importantly, attitudes can mold preferences for bicycling facilities. Those with a greater preference for automobiles and those who doubt the importance of exercise generally had lower perceptions of bicycling on all presented hypothetical roadways, while those who enjoy biking and with a greater risk tolerance had higher perceptions. Latent class models revealed different classes of relative preferences for different facilities that were largely dictated by these attitudinal factors. The models suggest that those who hold pro-bike attitudes can be split by risk-tolerance. While both groups preferred greater degrees of separation, those that were on the more conservative side of the risk were substantially more likely to give positive ratings to protected facilities. For those in this group, the difference was illustrative of the necessity for protected facilities, compared to the mild preference for these facilities shown by those in the more risk-embracing pro-cyclist group.

7.1.3 What role do additional bicycle facilities play in behavior and perceptions?

The analyses in Chapter 6 focused on those who responded to both waves of the survey and (1) how their behavior and attitudes changed between the two waves and (2) their perceptions of changes in their community after the fact. Unfortunately, there were very few respondents who made major changes to their bicycling behaviors, which limited the answer to the first half of this question to only anecdotal observations of several subjects who did increase their bicycling frequency. However, analysis of perceptions of changes revealed that those in areas with bicycling facility additions were much more likely to rate the bicycling safety and the availability and quality of bicycle trails and facilities as having improved over that timeframe. Even for those in communities where only low-quality treatments were implemented, the perceptions of improvement in the bikability of their community were higher than in their respective control communities.

7.2 Limitations

Despite the major contributions resulting from this research, there are still some nontrivial limitations. These limitations stem from the difficulty in measuring changes in bicycling behavior given the scope of the projects, as well as from issues in the reliability of relating stated preferences to actual behavior.

Although great effort was taken to obtain the highest-quality dataset reasonably possible, the data was still unable to inform one of the major questions on the outset: "If you build it, will cyclists come?" It is likely that the ability for this study to answer this fundamental question was severely limited by the small scale of projects in the study areas, the lack of high-quality facilities (such as protected bike lanes), and the relatively short time frame. Study sites were chosen to include an assortment of high-quality facilities but were ultimately down-graded to fairly low-quality treatments of short distances. It is not realistic that these small changes would be expected to result in a large number of residents increasing bicycling in a short time frame, especially when they do not form or connect into an expansive network. Changes in travel behavior occur over an extended period of time, so it seems that specific research studies may be unable to fully capture these effects, indicating a need for long-term data collection and analysis, possibly conducted by municipalities to measure trends throughout time.

Other limitations of this research include the hypothetical nature of stated preference studies. Although Atlanta, Birmingham, and Chattanooga have a supply of bike infrastructure more closely aligning with the facilities presented in the surveys and Northport has several trails, most residents in the sample likely would not have seen many of the presented infrastructure types, adding to the hypothetical challenges in this study. Thus, there is a question of how perceptions will change based on how familiar a respondent is with said facility. Aside from the issues of hypotheticality of facilities, the practice of modeling perceptions and preferences is a fairly abstract art in and of itself. Readers familiar with modeling more concrete concepts may be disheartened by the relatively weak measures of fit for many of the models in this dissertation, though most of the models presented herein have comparable fits to other disaggregate travel-behavior-related models in the literature, with some being rather exceptional.

7.3 Future Work

The findings from this study raise a much-needed voice from areas of the U.S. without a strong cycling presence. Although this research includes only a handful of locations from one geographic region, the survey used in this study was written for general application in other locations, and the reports for the two related projects (NCHRP and GDOT) encourage readers to duplicate parts of or the entire survey and/or to reach out to us for collaboration opportunities across additional sites to improve the representativeness of study sites with respect to more potential variables.

Even the dataset from these ten study communities still has vast quantities of high-quality data to be used for additional analyses. Future analyses include an investigation of how recognition and usage of treatment facilities impact various perceptions. Other possible analyses to be pursued are the investigation of valuation of time spent traveling and its relationship to perceptions of travel by various modes as well as mode preferences and changes in perceptions of bicycling based on distance to bicycling facilities before facility treatments.

Lessons learned from the completion of the research of this dissertation also inform future research directions. Since perceptions in this research were observed to change, but were not accompanied by changes in behavior, future research projects will be designed to encourage investigation of the things that can trigger an individual to make major changes in travel behavior, such as acquiring/losing vehicles, changes in employment, or relocating residence.

Although the research described in this dissertation came short of finding a satisfactory answer to the question “If you build it, will people use it?” for communities with underdeveloped bicycling facility networks and bicycling culture, there is still positive insight that can guide future attempts at this topic. The studying of only a handful of communities at only two points in time was not able to detect much in terms of changes in behavior, severely limiting the ability to attribute changes in behavior to infrastructure development. Such studies may be more appropriately implemented by—or in partnership with—municipal constituents. This approach may be more able to make consistent measurements over the course of time to methodically collect data on small changes in behavior and infrastructure over a longer period of time to allow for a more holistic analysis of the relationship between bicycling behavior and infrastructure development. These entities would be able to overcome some major challenges faced in this research relating to lack of control on project scope and timeline shifts. Perhaps if city, state, and other local officials take a more prominent role in this investigation, they will be able to unlock the passageway to being able to answer the question “If you build it, will people use it?” in their own cities and states.

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APPENDIX A.FIRST-WAVE SURVEY INSTRUMENT

Community Transportation Study

Thanks for taking our survey! Remember, we are interested in your answer to **each** question, even those dealing with topics that might be less familiar to you. If you have any questions, please feel free to contact my study team at survey@ce.gatech.edu, or me at kari.watkins@ce.gatech.edu, or call toll-free *1-855-444-2930*.

Alternatively, you may take the survey online at http://bit.ly/GTtranspo, with access code: **{code}**

To make sure we count your opinions, please complete the survey by ***May 12, 2017*** and send it back to us in the postage-paid envelope provided. If you are unable to fill out the survey by then, we would still welcome it as soon as you can. After completion of the survey, we'll send you a $2 bill as a token of gratitude. Thanks again!

Part A: Your Views on Various Topics

To begin, we'd like to learn more about your opinions on various issues related to travel and lifestyles. This will help us understand your answers to later questions. We want your true opinion on each statement, or your best guess for topics you are not very familiar with. Remember, **there are no "right" or "wrong" answers!**

1. For each of the following statements, please choose the response that most closely fits your reaction.

	Strongly disagree	*Disagree*	*Neutral or No opinion*	*Agree*	*Strongly agree*
I like the idea of living in a neighborhood where I can walk to the grocery store.	☐	☐	☐	☐	☐
The importance of exercise is overrated.	☐	☐	☐	☐	☐
Owning a car is an important sign of my freedom.	☐	☐	☐	☐	☐
Most drivers don't seem to notice bicyclists.	☐	☐	☐	☐	☐
Taking risks fits my personality.	☐	☐	☐	☐	☐
I'm often in a hurry to be somewhere else.	☐	☐	☐	☐	☐
This country has gone too far in its efforts to protect the environment.	☐	☐	☐	☐	☐
I generally enjoy the act of traveling itself.	☐	☐	☐	☐	☐
Around here, adults who bicycle for transportation are viewed as odd.	☐	☐	☐	☐	☐
The functionality of a car is more important to me than its brand.	☐	☐	☐	☐	☐
I can usually find good ways to use the time I spend traveling each day.	☐	☐	☐	☐	☐
I like to be among the first people to have the latest technology.	☐	☐	☐	☐	☐
I am trying to have an environmentally-friendly lifestyle.	☐	☐	☐	☐	☐
Most bicyclists look like they spend a lot of money on their bikes.	☐	☐	☐	☐	☐
I like trying things that are new and different.	☐	☐	☐	☐	☐

	Strongly disagree	*Disagree*	*Neutral or No opinion*	*Agree*	*Strongly agree*
I am usually very cautious with strangers.	☐	☐	☐	☐	☐
I like traveling by car.	☐	☐	☐	☐	☐
It's pretty hard for my friends to get me to change my mind.	☐	☐	☐	☐	☐
Kids often ride bicycles around my neighborhood for fun.	☐	☐	☐	☐	☐
My time spent in everyday travel is generally wasted time.	☐	☐	☐	☐	☐
I'm too busy to do many things I'd like to do.	☐	☐	☐	☐	☐
I like the idea of sometimes walking or biking instead of taking the car.	☐	☐	☐	☐	☐
I feel like I need to make the most of every single minute.	☐	☐	☐	☐	☐
Many bicyclists appear to have little regard for their personal safety.	☐	☐	☐	☐	☐
I am fine with not owning a car, as long as I can use/rent one any time I need it.	☐	☐	☐	☐	☐
Improving sidewalks should be a priority for my town.	☐	☐	☐	☐	☐
The only good thing about traveling is arriving at your destination.	☐	☐	☐	☐	☐
Most bicyclists look like they are too poor to own a car.	☐	☐	☐	☐	☐
I like using public transit when it provides good service.	☐	☐	☐	☐	☐
Getting regular exercise is very important to me.	☐	☐	☐	☐	☐
My dream is to live in a large house with a big yard.	☐	☐	☐	☐	☐
I would bicycle more if my friends / family came with me.	☐	☐	☐	☐	☐
I avoid doing things that I know my friends would dislike.	☐	☐	☐	☐	☐
I prefer to minimize the material goods I possess.	☐	☐	☐	☐	☐
Our first concern for transportation should be helping cars get around better.	☐	☐	☐	☐	☐
My phone is so important to me, it's almost a part of my body.	☐	☐	☐	☐	☐
I like bicycling.	☐	☐	☐	☐	☐
I am generally satisfied with my life.	☐	☐	☐	☐	☐

Part B: Technology in Your Life

In this short section, we are interested in learning about your online preferences and habits, and understanding how they relate to your lifestyles and travel choices.

1. Do you **regularly use** any of the following devices (for work or personal purposes)? Please respond to each.

	Yes	*No*
Smartphone	☐	☐
Basic (non-smartphone) cell phone	☐	☐
Laptop	☐	☐
Desktop computer	☐	☐
Tablet (e.g., iPad, Galaxy Tab)	☐	☐
Wearable technology (e.g., Apple Watch, Fitbit)	☐	☐

2. How often do you use a **computer** or **smartphone app** to do each of the following things?

	Seldom or never	*Several times a year*	*At least once a month*	*At least once a week*	*(Almost) every day*
Check traffic to plan my route or departure time	☐	☐	☐	☐	☐
Check bus / train arrivals	☐	☐	☐	☐	☐
Decide which means of transportation to use for a trip	☐	☐	☐	☐	☐
Identify possible destinations (e.g., restaurant, store)	☐	☐	☐	☐	☐
Learn how to get to a new place	☐	☐	☐	☐	☐
Navigate in real time (e.g., using Garmin, Waze)	☐	☐	☐	☐	☐
Check the weather	☐	☐	☐	☐	☐

Part C: The Place You Call Home

Learning more about your home will help us understand how these factors affect the way you organize your daily activities and the way you travel.

1. What best describes the type of residence you currently live in? Please check one.

☐ Detached (free-standing) home
☐ Attached home / duplex / townhouse
☐ Apartment /condo building
☐ Dormitory
☐ Other (please specify): ____________

2. In what year (YYYY) did you move to your current address?

Year: ________

☐ I have lived here my entire life

3. Knowing more about your general neighborhood will help us put your transportation choices and opinions in context. Please give your address or, if you prefer, an intersection (two streets that cross) near your home.

___________________________________ (and ___________________________________)

City: _______________________________ Zip code: _______________________________

4. Who lives with you? Please check all that apply:

- ☐ My partner / husband / wife
- ☐ My child(ren) or grandchild(ren)
- ☐ My parent(s) or grandparent(s)
- ☐ One or more of my siblings
- ☐ Some other relative(s)
- ☐ One or more roommates / housemates
- ☐ I live alone
- ☐ Other (please specify): _______________

Part D: Your Daily Travel

Please think about your everyday travel: where you go to work or school, shop, and relax. We're interested in learning about your typical transportation choices.

1. On average, how many days per week do you do each of the following? By **telecommuting**, we mean **working / studying** from home or a nearby location (not counting overtime work at home).

Travel to **work:** ____ days/wk ☐ Not applicable

Travel to **school:**____ days/wk ☐ Not applicable

Telecommute: ____ days/wk ☐ Not applicable

For the following block of questions, please consider the regular trip to your main **work** / **school** location. If you travel to **more than one location** on a regular basis, consider the location to which you travel most often.

→ If you do NOT travel to **work or school** at all, please go to **question 7 of Part D, page 5**

2. How far do you live from your main **work** / **school** destination? _______ miles

3. How long does it usually take you to get from home to **work** / **school** (one-way trip)? _____ minutes

4. Knowing more about where you **work** / **study** will help us better understand the transportation options that are available to you. Please give the address or, if you prefer, an intersection (two streets that cross) that is close to your **main work** / **school location**.

___________________________________ (and ___________________________________)

City: _______________________________ Zip code: _______________________________

5. In terms of its **value to you**, how would you rate the time you typically spend on your **work** / **school** trip? Place a mark (×) at the most appropriate place on the scale below:

Mostly wasted time |———|———|———|———|———| *Mostly useful time*

6. Considering your **trips to work / school**, please indicate **how often** you use each of the following means of transportation for such trips:

	Never	*Less than once a **month***	*1-3 days a **month***	*1-2 days a **week***	*3-4 days a **week***	*5 or more days a **week***
Alone in personal car, truck, van, or motorcycle	☐	☐	☐	☐	☐	☐
With others in car, van...	☐	☐	☐	☐	☐	☐
Public transit	☐	☐	☐	☐	☐	☐
Taxi	☐	☐	☐	☐	☐	☐
Uber, Lyft, etc.	☐	☐	☐	☐	☐	☐
Bicycle	☐	☐	☐	☐	☐	☐
Walk	☐	☐	☐	☐	☐	☐
Other: ___________	☐	☐	☐	☐	☐	☐

7. Consider your **trips for other** (non-work / school) **purposes** (e.g., for grocery or clothes shopping, going to a restaurant/bar or ball game, attending church, visiting others, running errands, or for hobbies). Please indicate **how often** you typically make such trips, using each of the following means of transportation:

	Never	*Less than once a **month***	*1-3 days a **month***	*1-2 days a **week***	*3-4 days a **week***	*5 or more days a **week***
Alone in personal car, truck, van, or motorcycle	☐	☐	☐	☐	☐	☐
With others in car, van...	☐	☐	☐	☐	☐	☐
Public transit	☐	☐	☐	☐	☐	☐
Taxi	☐	☐	☐	☐	☐	☐
Uber, Lyft, etc.	☐	☐	☐	☐	☐	☐
Bicycle	☐	☐	☐	☐	☐	☐
Walk	☐	☐	☐	☐	☐	☐
Other: ____________	☐	☐	☐	☐	☐	☐

8. Thinking about all your travel, would you **like** to travel **more** or **less** by the following **means of transportation,** and for the following **purposes**? Please respond for **each means** and **each purpose**.

I'd like to travel:	*Less*	*About the same*	*More*
By car/truck/van /motorcycle	☐	☐	☐
By public transit	☐	☐	☐
By bicycle	☐	☐	☐
By walking	☐	☐	☐
By other: _______	☐	☐	☐

I'd like to travel:	*Less*	*About the same*	*More*
For work / school	☐	☐	☐
For shopping	☐	☐	☐
For social	☐	☐	☐
For entertainment	☐	☐	☐
For eating out	☐	☐	☐
For other:______	☐	☐	☐

With respect to **how well they meet your current needs**, please rate the four most common means of travel on each of the following attributes. We are interested in your views on **each**, even **if you seldom** or **never use** some of these means.

Personal vehicle (e.g., car, truck, van, motorcycle)	*Very bad*	*Bad*	*Neutral or No opinion*	*Good*	*Very good*
Overall rating as a means of travel for me	☐	☐	☐	☐	☐
Comfort	☐	☐	☐	☐	☐
Ability to get where I need or want to go	☐	☐	☐	☐	☐
Reliability	☐	☐	☐	☐	☐
Safety / security	☐	☐	☐	☐	☐
Effect on the environment	☐	☐	☐	☐	☐
Cost	☐	☐	☐	☐	☐
Availability when needed / wanted	☐	☐	☐	☐	☐
Traveling in poor weather conditions	☐	☐	☐	☐	☐
Ability to stop at additional places on the same trip	☐	☐	☐	☐	☐
Avoiding congestion	☐	☐	☐	☐	☐
Privacy	☐	☐	☐	☐	☐
Ability to carry things with me	☐	☐	☐	☐	☐
Ability to spend travel time in useful ways	☐	☐	☐	☐	☐
Ability to relax / have fun while traveling	☐	☐	☐	☐	☐

Public transportation (e.g., local bus)	*Very bad*	*Bad*	*Neutral or No opinion*	*Good*	*Very good*
Overall rating as a means of travel for me	☐	☐	☐	☐	☐
Comfort	☐	☐	☐	☐	☐
Ability to get where I need or want to go	☐	☐	☐	☐	☐
Reliability	☐	☐	☐	☐	☐
Safety / security	☐	☐	☐	☐	☐
Effect on the environment	☐	☐	☐	☐	☐
Cost	☐	☐	☐	☐	☐
Availability when needed/ wanted	☐	☐	☐	☐	☐
Traveling in poor weather conditions	☐	☐	☐	☐	☐
Ability to stop at additional places on the same trip	☐	☐	☐	☐	☐
Avoiding congestion	☐	☐	☐	☐	☐
Privacy	☐	☐	☐	☐	☐
Ability to carry things with me	☐	☐	☐	☐	☐
Ability to spend travel time in useful ways	☐	☐	☐	☐	☐
Ability to relax / have fun while traveling	☐	☐	☐	☐	☐

Remember, we want your considered opinions on each means of travel, **even if you never use** some of them.

Bicycling	*Very bad*	*Bad*	*Neutral or No opinion*	*Good*	*Very good*
Overall rating as a means of travel for me	☐	☐	☐	☐	☐
Comfort	☐	☐	☐	☐	☐
Ability to get where I need or want to go	☐	☐	☐	☐	☐
Reliability	☐	☐	☐	☐	☐
Safety / security	☐	☐	☐	☐	☐
Effect on the environment	☐	☐	☐	☐	☐
Cost	☐	☐	☐	☐	☐
Availability when needed/ wanted	☐	☐	☐	☐	☐
Traveling in poor weather conditions	☐	☐	☐	☐	☐
Ability to stop at additional places on the same trip	☐	☐	☐	☐	☐
Avoiding congestion	☐	☐	☐	☐	☐
Privacy	☐	☐	☐	☐	☐
Ability to carry things with me	☐	☐	☐	☐	☐
Ability to spend travel time in useful ways	☐	☐	☐	☐	☐
Ability to relax / have fun while traveling	☐	☐	☐	☐	☐

Walking	*Very bad*	*Bad*	*Neutral or No opinion*	*Good*	*Very good*
Overall rating as a means of travel for me	☐	☐	☐	☐	☐
Comfort	☐	☐	☐	☐	☐
Ability to get where I need or want to go	☐	☐	☐	☐	☐
Reliability	☐	☐	☐	☐	☐
Safety / security	☐	☐	☐	☐	☐
Effect on the environment	☐	☐	☐	☐	☐
Cost	☐	☐	☐	☐	☐
Availability when needed/ wanted	☐	☐	☐	☐	☐
Traveling in poor weather conditions	☐	☐	☐	☐	☐
Ability to stop at additional places on the same trip	☐	☐	☐	☐	☐
Avoiding congestion	☐	☐	☐	☐	☐
Privacy	☐	☐	☐	☐	☐
Ability to carry things with me	☐	☐	☐	☐	☐
Ability to spend travel time in useful ways	☐	☐	☐	☐	☐
Ability to relax / have fun while traveling	☐	☐	☐	☐	☐

On the next two pages, we portray six different kinds of bikeways in use today. Please look at the images carefully and answer a few questions for each one.

Sharrows on road with parking

Sharrows ("share arrows") show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road without parking

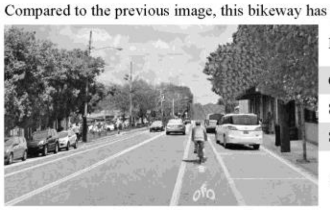
A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road with parking

Compared to the previous image, this bikeway has parked cars on the right side of the bike lane. Please mark your reaction to **each** statement below:



Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 1 Images (2)

Buffered bike lane on road without parking

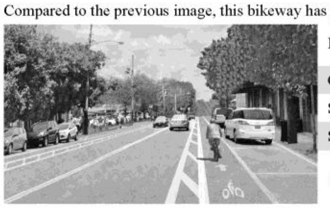
A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Buffered bike lane on road with parking

Compared to the previous image, this bikeway has parked cars on the right side of the buffered bike lane. Please mark your reaction to **each** statement below:

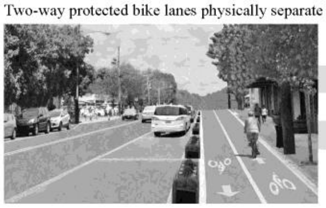


Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Two-way protected bike lanes on road with parking

Two-way protected bike lanes physically separate bicyclists (coming from both directions) from motorists. Please mark your reaction to **each** statement below:



Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 2 Images (1)

Sharrows on 2-lane road

Sharrows ("share arrows") show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on 2-lane road

A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Buffered bike lane on 2-lane road

A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 2 Images (2)

Buffered bike lane on 4-lane road

Compared to the previous image, this bikeway is placed next to a 4-lane road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Protected bike lane on 2-lane road

A protected bike lane is an exclusive bike lane that physically separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Multi-use trail

A multi-use trail is a dedicated path for bicyclists and pedestrians that is completely separate from the road. Please mark your reaction to **each** statement below:

Bicycling on a trail like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a trail like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 3 Images (1)

Sharrows on 4-lane road

Sharrows ("share arrows") show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on 2-lane road

A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on 4-lane road

Compared to the previous image, this bikeway is placed next to a 4-lane road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 3 Images (2)

Buffered bike lane on 4-lane road

A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Protected bike lane on 4-lane road

A protected bike lane is an exclusive bike lane that physically separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Multi-use trail

A multi-use trail is a dedicated path for bicyclists and pedestrians that is completely separate from the road. Please mark your reaction to **each** statement below:

Bicycling on a trail like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a trail like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 4 Images (1)

Sharrows on road without parking

Sharrows (“share arrows”) show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I’d try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road without parking

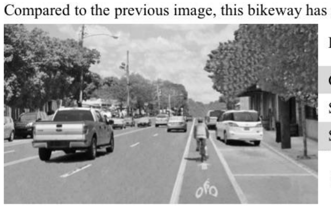
A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I’d try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road with parking

Compared to the previous image, this bikeway has parked cars on the right side of the bike lane. Please mark your reaction to **each** statement below:



Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I’d try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 4 Images (2)

Buffered bike lane on road without parking

A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Two-way protected bike lanes on road without parking

Two-way protected bike lanes physically separate bicyclists (coming from both directions) from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Multi-use trail

A multi-use trail is a dedicated path for bicyclists and pedestrians that is completely separate from the road. Please mark your reaction to **each** statement below:

Bicycling on a trail like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a trail like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Part E: Your Bicycling Experience

Bicycling is one activity that is gaining more attention, and new bikeways are being installed in many cities. Whether you love it, hate it, or don't care – we're interested in your opinions about bicycling.

1. How would you rate your ability to ride a bicycle? Please indicate your confidence level, regardless of whether it is practical or desirable for you to ride a bicycle nowadays.

   ☐ I cannot ride a bike at all ➔ Please go to **question 4 below**.
   ☐ I can ride a bike, but I am not very confident doing so
   ☐ I am somewhat confident riding a bike
   ☐ I am very confident riding a bike

2. On average, how many miles do you ride a bicycle? ☐ I (almost) never ride a bicycle

   For completely **recreational** purposes: ______ miles per **week** ***OR*** ______ miles per **month**
   For **practical** purposes
   (e.g., to go to **work** / **school**, to the store) : ______ miles per **week** ***OR*** ______ miles per **month**

3. Regardless of how you *currently* get there, which of the following factors make it more difficult for you to travel to **work** / **school** by bicycling? Place a mark (×) at the appropriate place on the scale for each statement below:

	Does not limit ⟺ *Absolutely prevents*	*Does not apply*
The location is too far to be reached by bicycle	|——|——|——|——|	☐
Weather (e.g., rain, heat, cold)	|——|——|——|——|	☐
It is too slow	|——|——|——|——|	☐
It takes too much physical effort	|——|——|——|——|	☐
Safety / security concerns (e.g., traffic, accidents)	|——|——|——|——|	☐
Need to make multiple trips	|——|——|——|——|	☐
Negative effect on appearance (e.g., sweat, hair)	|——|——|——|——|	☐
Difficult to carry bags/heavy packages with me	|——|——|——|——|	☐
Difficult to travel with children	|——|——|——|——|	☐
Other (please specify): ____________________	|——|——|——|——|	☐

4. When it comes to bicycling, what are your experiences and future choices with respect to these activities? Please check the **single most appropriate answer** for **each** activity below:

	*I **do** it now*		***OR*** *I've **done** it*		***OR*** *I've **never done** it*	
	*& **might continue***	*& **won't continue***	*& **might do** it again*	*& **won't do** it again*	*& **might do** it*	*& **won't do** it*
Bicycling to work / school	☐	☐	☐	☐	☐	☐
Bicycling to go other places	☐	☐	☐	☐	☐	☐
Bicycling for fun / exercise	☐	☐	☐	☐	☐	☐
Bicycling in bad weather	☐	☐	☐	☐	☐	☐
Using bikeshare services	☐	☐	☐	☐	☐	☐

Part F: Some Background about Yourself

This is the last section of the survey. We're almost done! To help us know you a little bit better, we'd like to ask you a few background questions.

1. How old were you on January 1, 2017? _______ years old

2. Where did you grow up? Please indicate the single US state or territory, or foreign country, where you lived for the longest period of time as a child / teenager. ___________________

3. Overall, how would you describe the area where you were raised?

   - ☐ Small town/ rural area
   - ☐ Suburban area
   - ☐ Core of a small urban area (e.g., population less than 1 million)
   - ☐ Core of a large urban area (e.g., population over 1 million)

4. What is your gender identity?

   - ☐ Female
   - ☐ Male
   - ☐ Prefer not to answer
   - ☐ Other (please specify):__________

5. Would you describe yourself as… (please check all that apply)

   - ☐ American Indian/Native American
   - ☐ Asian/Pacific Islander
   - ☐ Black/African American
   - ☐ Hispanic/Latino
   - ☐ White/Caucasian
   - ☐ Prefer not to answer
   - ☐ Other (please specify): __________

6. Do you have a driver's license? ☐ Yes ☐ No

7. Are you a current student? ☐ Yes, full-time ☐ Yes, part-time ☐ No

8. What is your educational background? Please check the **highest level attained**.

   - ☐ Some grade / some high school
   - ☐ High school / GED
   - ☐ Some college / technical school
   - ☐ Associate's degree
   - ☐ Bachelor's degree
   - ☐ Graduate degree (e.g., MS, PhD, MBA)
   - ☐ Professional degree (e.g., JD, MD, DDS)
   - ☐ Prefer not to answer

9. Which statements describe your current employment situation? Please check all that apply:

   - ☐ I work full-time
   - ☐ I work part-time
   - ☐ I have two or more jobs
   - ☐ I am a homemaker/ unpaid caregiver
   - ☐ I do not work

   → Please go to the **next page**.

10. Which option best describes your main occupation?

    - ☐ Professional/technical
    - ☐ Manager/administrator
    - ☐ Sales/marketing
    - ☐ Production/construction
    - ☐ Service/repair
    - ☐ Clerical/administrative support
    - ☐ Other (please specify): ________________

11. On average, **how many hours** in a week do you work **for pay**? _______ hours per week

For the following questions, please remember that by **"household"** we mean, "people who live together and share at least some financial resources" (ordinary housemates/ roommates are usually **not** considered members of the same household).

12. **Including yourself**, how many people live in your household? _____ people

13. **Including yourself**, how many people in your household fall into **each** of the age groups listed below? If there is no one in a particular age group, please respond with zero ("0") for that age group.

_____ persons under 6 years old
_____ persons 6-12
_____ persons 13-17
_____ persons 18-26
_____ persons 27-34
_____ persons 35-50
_____ persons 51-65
_____ persons 66-75
_____ persons over the age of 75
☐ Prefer not to answer

14. **Including yourself**, how many people in your household hold a driver's license? _____ people

15. How many motorized vehicles (e.g., cars, vans, motorcycles) does your household have? _____ vehicles

16. How many bicycles does your household have? If none, please write "0". _____ bicycles

17. Please check the category that contains your approximate annual **household income** before taxes:

☐ $15,000 or less
☐ $15,001 to $30,000
☐ $30,001 to $50,000
☐ $50,001 to $75,000
☐ $75,001 to $100,000
☐ $100,001 to $125,000
☐ More than $125,000
☐ Prefer not to answer

18. In 2017 and 2018 your community may experience changes in transportation, and it is important for us to know your opinions on these changes. To help us reach you for the **follow-up survey next year**, it would be useful to have your email address if you have one. In addition, if you are willing to be contacted in case we have any questions about your survey, we would appreciate having your phone number. All of this information is kept completely confidential, and will never be used for any other purpose.

Email: ______________________________ Phone: ____________________

Thank you for your time!

We welcome any additional comments you may have regarding transportation in your community. Please write them in the space below, and on additional sheets of paper if needed.

APPENDIX B. SECOND-WAVE SURVEY INSTRUMENT

School of Civil and Environmental Engineering

April 30, 2018

Dear <resident> or current resident:

Georgia Tech is leading a study of transportation in your community. You or a member of your household completed a previous survey for this study in Spring 2017, and we are now following up regarding how your travel may have changed since then. We are interested in your daily travel and the things that can cause it to change over time, which is why we are asking you to participate in this shorter survey even though you may have completed the previous one. The findings of this study will inform transportation planning throughout the Southeast and across the nation.

Your participation in this study is voluntary, but your responses are ***extremely*** important to us. The questionnaire will take about 20 minutes to complete, and we think you'll find the content interesting. We ask that the survey be filled out by the same adult (19 years old or older) as before. However, if that person is unable to participate, another adult in the household may do so. Please limit your response to one survey per household.

Study records will be kept confidential to the extent allowed by law, and all identifying information will be kept in a secure location at Georgia Tech. The risks involved in participating are no greater than those involved in daily activities. You do not waive any of your legal rights by agreeing to be in the study.

After completion of the survey, we'll send you a $2 bill as a token of our gratitude. You won't receive any other personal benefits for participating, aside from the satisfaction of contributing to better transportation planning.

To ensure the timely inclusion of your responses in the study, we kindly ask you to complete the survey by ***May 25, 2018.*** If you are unable to fill out the questionnaire by then, we would still welcome it as soon as you can. You may complete the printed copy included and return it back to us in the postage-paid envelope provided, or, alternatively, we encourage you to take the survey online at the following website:

http://bit.ly/transpo2018

To access the online survey, please enter your invitation five-letter code:

<code>

If you have questions about the study, please email my study team at survey@ce.gatech.edu or me personally at kari.watkins@ce.gatech.edu, or call toll-free *1-855-444-2930*. If you have any questions about your rights as a research subject, you may contact Ms. Melanie Clark, Georgia Institute of Technology at (404) 894-6942. Thank you in advance for your time and for sharing your thoughts and opinions with us.

Thank you,

Kari E. Watkins

Dr. Kari Edison Watkins, PhD, PE
Associate Professor

School of Civil and Environmental Engineering
Atlanta, GA 30332-0355 U.S.A.
Phone 404-894-2201

Part A: Your Views on Various Topics

To begin, we ask for your opinions on some travel and lifestyle topics. Even if you responded to similar items in the previous survey, we'd like to know your current thoughts on each item, including your best guesses on topics that are less familiar to you. Remember, **there are no "right" or "wrong" answers!**

1. For each of the following statements, please choose the response that most closely fits your reaction.

	Strongly disagree	*Disagree*	*Neutral or No opinion*	*Agree*	*Strongly agree*
I like the idea of living in a neighborhood where I can walk to the grocery store.	☐	☐	☐	☐	☐
The importance of exercise is overrated.	☐	☐	☐	☐	☐
Owning a car is an important sign of my freedom.	☐	☐	☐	☐	☐
Most drivers don't seem to notice bicyclists.	☐	☐	☐	☐	☐
The functionality of a car is more important to me than its brand.	☐	☐	☐	☐	☐
I'm often in a hurry to be somewhere else.	☐	☐	☐	☐	☐
This country has gone too far in its efforts to protect the environment.	☐	☐	☐	☐	☐
I generally enjoy the act of traveling itself.	☐	☐	☐	☐	☐
Around here, adults who bicycle for transportation are viewed as odd.	☐	☐	☐	☐	☐
Taking risks fits my personality.	☐	☐	☐	☐	☐
I can usually find good ways to use the time I spend traveling each day.	☐	☐	☐	☐	☐
I like to be among the first people to have the latest technology.	☐	☐	☐	☐	☐
I am trying to have an environmentally-friendly lifestyle.	☐	☐	☐	☐	☐
Most bicyclists look like they spend a lot of money on their bikes.	☐	☐	☐	☐	☐
I like trying things that are new and different.	☐	☐	☐	☐	☐
It's pretty hard for my friends to get me to change my mind.	☐	☐	☐	☐	☐
I like traveling by car.	☐	☐	☐	☐	☐
Kids often ride bicycles around my neighborhood for fun.	☐	☐	☐	☐	☐
I am usually very cautious with strangers.	☐	☐	☐	☐	☐
My time spent in everyday travel is generally wasted time.	☐	☐	☐	☐	☐
I'm too busy to do many things I'd like to do.	☐	☐	☐	☐	☐
I like the idea of sometimes walking or biking instead of taking the car.	☐	☐	☐	☐	☐

	Strongly disagree	*Disagree*	*Neutral or No opinion*	*Agree*	*Strongly agree*
I feel like I need to make the most of every single minute.	☐	☐	☐	☐	☐
Many bicyclists appear to have little regard for their personal safety.	☐	☐	☐	☐	☐
I am fine with not owning a car, as long as I can use/rent one any time I need it.	☐	☐	☐	☐	☐
Improving sidewalks should be a priority for my town.	☐	☐	☐	☐	☐
The only good thing about traveling is arriving at your destination.	☐	☐	☐	☐	☐
Most bicyclists look like they are too poor to own a car.	☐	☐	☐	☐	☐
I like using public transit when it provides good service.	☐	☐	☐	☐	☐
Getting regular exercise is very important to me.	☐	☐	☐	☐	☐
My dream is to live in a large house with a big yard.	☐	☐	☐	☐	☐
I would bicycle more if my friends / family came with me.	☐	☐	☐	☐	☐
I avoid doing things that I know my friends would dislike.	☐	☐	☐	☐	☐
I prefer to minimize the material goods I possess.	☐	☐	☐	☐	☐
I like bicycling.	☐	☐	☐	☐	☐
My phone is so important to me, it's almost a part of my body.	☐	☐	☐	☐	☐
Our first concern for transportation should be helping cars get around better.	☐	☐	☐	☐	☐
I am generally satisfied with my life.	☐	☐	☐	☐	☐

Part B: Your Daily Travel

Please think about your everyday travel: where you go to work or school, shop, and relax. We're interested in learning about your typical transportation choices.

1. Are you a current student? ☐ Yes, full-time ☐ Yes, part-time ☐ No

2. Which statements describe your current employment situation? Please check all that apply:

   ☐ I work full-time
   ☐ I work part-time
   ☐ I have two or more jobs
   ☐ I am a homemaker/ unpaid caregiver
   ☐ I do not work/ I am retired

If you do NOT **work or attend school** at all, please go to **question 10 of Part B, page 5** →

If you **work OR attend school,** please respond to the following questions about your work or school experience and commute.

3. On average, **how many hours** in a week do you work **for pay**? _______ hours per week

4. On average, how many days per week do you do each of the following? By **telecommuting**, we mean **working / studying** from home or a nearby location (not counting overtime work at home).

Travel to **work:** ____ days/wk
☐ Not applicable

Travel to **school:** ____ days/wk
☐ Not applicable

Telecommute: ____ days/wk
☐ Not applicable

5. How far do you live from your main **work / school** destination? _______ miles

6. How long does it usually take you to get from home to **work / school** (one-way trip)? _____ minutes

7. Knowing more about where you **work / study** will help us understand the transportation options available. Please give the address or, if you prefer, an intersection (two streets that cross) close to your **main work / school location**. If you travel to **more than one location** on a regular basis, consider the location to which you travel most often.

__________________________________ (and __________________________________)

City: ______________________________ Zip code: ______________________________

8. In terms of its **value to you**, how would you rate the time you typically spend on your **work / school** trip? Place a mark (×) at the most appropriate place on the scale below:

Mostly wasted time |——————|——————|——————|——————|——————| *Mostly useful time*

9. Considering your **trips to work / school**, please indicate **how often** you use each of the following means of transportation for such trips:

	Never	*Less than once a **month***	*1-3 days a **month***	*1-2 days a **week***	*3-4 days a **week***	*5 or more days a **week***
Alone in personal car, truck, van, or motorcycle	☐	☐	☐	☐	☐	☐
With others in car, van...	☐	☐	☐	☐	☐	☐
Public transit	☐	☐	☐	☐	☐	☐
Taxi	☐	☐	☐	☐	☐	☐
Uber, Lyft, etc.	☐	☐	☐	☐	☐	☐
Bicycle	☐	☐	☐	☐	☐	☐
Walk	☐	☐	☐	☐	☐	☐
Other: ___________	☐	☐	☐	☐	☐	☐

10. Consider your **trips for other** (non-work / school) **purposes** (e.g., for grocery or clothes shopping, going to a restaurant/bar or ball game, attending church, visiting others, running errands, or for hobbies). Please indicate **how often** you use each of the following means of transportation for such trips:

	Never	*Less than once a **month***	*1-3 days a **month***	*1-2 days a **week***	*3-4 days a **week***	*5 or more days a **week***
Alone in personal car, truck, van, or motorcycle	☐	☐	☐	☐	☐	☐
With others in car, van...	☐	☐	☐	☐	☐	☐
Public transit	☐	☐	☐	☐	☐	☐
Taxi	☐	☐	☐	☐	☐	☐
Uber, Lyft, etc.	☐	☐	☐	☐	☐	☐
Bicycle	☐	☐	☐	☐	☐	☐
Walk	☐	☐	☐	☐	☐	☐
Other: ____________	☐	☐	☐	☐	☐	☐

11. We would like to know whether transportation in your community has changed since <First Survey>, either for better or worse. Please give your opinion for each category below.

	Much worse	*Somewhat worse*	*Neutral/ No change*	*Somewhat better*	*Much better*
Traffic congestion	☐	☐	☐	☐	☐
Parking availability	☐	☐	☐	☐	☐
Public transit route coverage (can reach more/fewer places)	☐	☐	☐	☐	☐
Public transit frequency (comes more/less often)	☐	☐	☐	☐	☐
Sidewalk availability (more/fewer of them)	☐	☐	☐	☐	☐
Sidewalk quality	☐	☐	☐	☐	☐
Bicycle safety	☐	☐	☐	☐	☐
Availability of bicycle lanes and trails	☐	☐	☐	☐	☐
Quality of bicycle lanes and trails	☐	☐	☐	☐	☐
Availability of taxi/ Uber/ Lyft	☐	☐	☐	☐	☐
Other (please specify): ________________________	☐	☐	☐	☐	☐

On the next two pages, we portray six different kinds of bikeways in use today. Please look at the images carefully and answer a few questions for each one, even if you are not very interested in bicycling.

Version 1 Images (1)

Sharrows on road with parking

Sharrows ("share arrows") show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road without parking

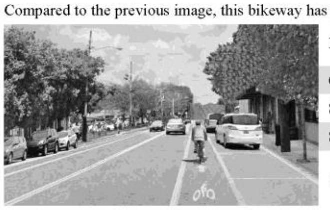
A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road with parking

Compared to the previous image, this bikeway has parked cars on the right side of the bike lane. Please mark your reaction to **each** statement below:



Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Buffered bike lane on road without parking

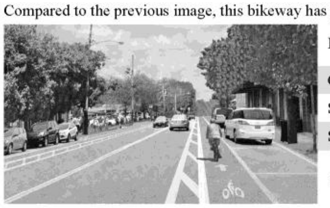
A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Buffered bike lane on road with parking

Compared to the previous image, this bikeway has parked cars on the right side of the buffered bike lane. Please mark your reaction to **each** statement below:

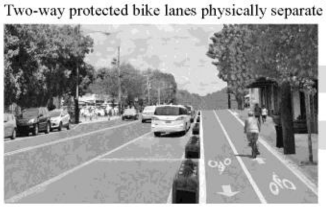


Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Two-way protected bike lanes on road with parking

Two-way protected bike lanes physically separate bicyclists (coming from both directions) from motorists. Please mark your reaction to **each** statement below:



Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 2 Images (1)

Sharrows on 2-lane road

Sharrows ("share arrows") show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on 2-lane road

A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Buffered bike lane on 2-lane road

A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 2 Images (2)

Buffered bike lane on 4-lane road

Compared to the previous image, this bikeway is placed next to a 4-lane road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Protected bike lane on 2-lane road

A protected bike lane is an exclusive bike lane that physically separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Multi-use trail

A multi-use trail is a dedicated path for bicyclists and pedestrians that is completely separate from the road. Please mark your reaction to **each** statement below:

Bicycling on a trail like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a trail like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 3 Images (1)

Sharrows on 4-lane road

Sharrows ("share arrows") show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on 2-lane road

A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on 4-lane road

Compared to the previous image, this bikeway is placed next to a 4-lane road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 3 Images (2)

Buffered bike lane on 4-lane road

A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Protected bike lane on 4-lane road

A protected bike lane is an exclusive bike lane that physically separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Multi-use trail

A multi-use trail is a dedicated path for bicyclists and pedestrians that is completely separate from the road. Please mark your reaction to **each** statement below:

Bicycling on a trail like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a trail like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 4 Images (1)

Sharrows on road without parking

Sharrows (“share arrows”) show that motorists and bicyclists will be sharing the road. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I’d try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road without parking

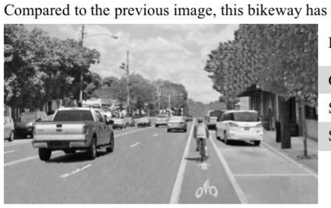
A bike lane is a dedicated lane for bicycling, separated with pavement markings only. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I’d try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Bike lane on road with parking

Compared to the previous image, this bikeway has parked cars on the right side of the bike lane. Please mark your reaction to **each** statement below:



Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I’d try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Version 4 Images (2)

Buffered bike lane on road without parking

A buffered bike lane is a bike lane with buffer space that separates bicyclists from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Two-way protected bike lanes on road without parking

Two-way protected bike lanes physically separate bicyclists (coming from both directions) from motorists. Please mark your reaction to **each** statement below:

Bicycling on a road like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a road like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Multi-use trail

A multi-use trail is a dedicated path for bicyclists and pedestrians that is completely separate from the road. Please mark your reaction to **each** statement below:

Bicycling on a trail like this is …	*Completely disagree*	*Disagree*	*Neutral*	*Agree*	*Completely agree*
Comfortable	☐	☐	☐	☐	☐
Safe	☐	☐	☐	☐	☐
Something I'd try	☐	☐	☐	☐	☐

How often have you bicycled on a trail like this? ☐ Never ☐ Sometimes ☐ Often ☐ Not sure

Part C: Your Bicycling Experience

Bicycling is one activity that is gaining more attention. Whether you love it, hate it, or don't care – we're interested in your opinions about bicycling.

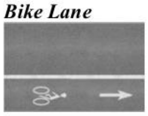
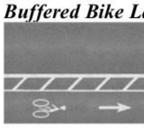
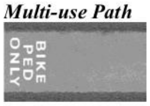
1. How would you rate your ability to ride a bicycle? Please indicate your confidence level, regardless of whether it is practical or desirable for you to ride a bicycle nowadays.

   ☐ I cannot ride a bike at all ⟶ Please go to **question 3 below**.
   ☐ I can ride a bike, but I am not very confident doing so
   ☐ I am somewhat confident riding a bike
   ☐ I am very confident riding a bike

2. On average, how many miles do you ride a bicycle… ☐ I (almost) never ride a bicycle

For completely **recreational** purposes?	______ miles per **week** ***OR*** ______ miles per **month**
For **practical** purposes (e.g., to go to work / school, to the store)?	______ miles per **week** ***OR*** ______ miles per **month**

3. Since <First Survey>, some communities in the US have added new bicycle infrastructure. Have you noticed the *addition* of any of the following features in your community?

	Have you seen this added in your community?			***If you've seen it…*** ***…have you used it?***			***…do you like it?***		
	No	*Not sure*	*Yes*	*No*	*Not sure*	*Yes*	*No*	*Neutral*	*Yes*
Sharrow 	☐	☐	☐	☐	☐	☐	☐	☐	☐
Bike Lane 	☐	☐	☐	☐	☐	☐	☐	☐	☐
Buffered Bike Lane 	☐	☐	☐	☐	☐	☐	☐	☐	☐
Protected Bike Lane 	☐	☐	☐	☐	☐	☐	☐	☐	☐
Multi-use Path 	☐	☐	☐	☐	☐	☐	☐	☐	☐

Part D: Some Background about Yourself

To help us know you a little bit better, we'd like to ask you a few background questions. Again, even if you answered these questions on the previous survey, we need to know if anything has changed.

1. How old were you on January 1, 2018? _______ years old

2. What is your gender identity?
   - ☐ Female
   - ☐ Male
   - ☐ Prefer not to answer
   - ☐ Other (please specify):__________

3. Would you describe yourself as… (please check all that apply)
   - ☐ American Indian/Native American
   - ☐ Asian/Pacific Islander
   - ☐ Black/African American
   - ☐ Hispanic/Latino
   - ☐ White/Caucasian
   - ☐ Prefer not to answer
   - ☐ Other (please specify): __________

4. Do you have a driver's license? ☐ Yes ☐ No

5. What is your educational background? Please check the **highest level attained**.
   - ☐ Some grade school / some high school
   - ☐ High school / GED
   - ☐ Some college / technical school
   - ☐ Associate's degree
   - ☐ Bachelor's degree
   - ☐ Graduate degree (e.g., MS, PhD, MBA)
   - ☐ Professional degree (e.g., JD, MD, DDS)
   - ☐ Prefer not to answer

6. What best describes the type of residence you currently live in? Please check one.
   - ☐ Detached (free-standing) home
   - ☐ Attached home / duplex / townhouse
   - ☐ Apartment /condo building
   - ☐ Dormitory
   - ☐ Other (please specify): __________

7. Knowing more about your general neighborhood will help us put your transportation choices and opinions in context. Please give your address or, if you prefer, an intersection (two streets that cross) near your home.

   ___________________________________ (and ___________________________________)

   City: _______________________________ Zip code: _______________________________

8. In what year (YYYY) did you move to your current address?

   Year: _____

9. Who lives with you? Please check all that apply:
   - ☐ My partner / husband / wife
   - ☐ My child(ren) or grandchild(ren)
   - ☐ My parent(s) or grandparent(s)
   - ☐ One or more of my siblings
   - ☐ Some other relative(s)
   - ☐ One or more roommates / housemates
   - ☐ I live alone
   - ☐ Other (please specify): _______________

For the following questions, we will ask you about your household; by **"household"** we mean, "people who live together and share at least some financial resources" (ordinary housemates/ roommates are **not** considered members of the same household).

10. **Including yourself**, how many people live in your household? _____ people

11. **Including yourself**, how many people in your household fall into **each** of the age groups listed below? If there is no one in a particular age group, please respond with zero ("0") for that age group.

_____ persons under 6 years old
_____ persons 6-12
_____ persons 13-17
_____ persons 18-26
_____ persons 27-34
_____ persons 35-50
_____ persons 51-65
_____ persons 66-75
_____ persons over the age of 75
☐ Prefer not to answer

12. **Including yourself**, how many people in your household hold a driver's license? _____ people

13. How many motorized vehicles (e.g., cars, vans, motorcycles) does your household have? _____ vehicles

14. How many bicycles does your household have? If none, please write "0". _____ bicycles

15. Please check the category that contains your approximate annual **household income** before taxes:

☐ $15,000 or less
☐ $15,001 to $30,000
☐ $30,001 to $50,000
☐ $50,001 to $75,000
☐ $75,001 to $100,000
☐ $100,001 to $125,000
☐ More than $125,000
☐ Prefer not to answer

16. In the coming months and years, your community may experience further changes in transportation, and we may want to ask for your opinions about these changes. To help us reach you for occasional **follow-up surveys in the future**, it would be useful to have your email address if you have one. In addition, if you are willing to be contacted in case we have any questions about your survey, we would appreciate having your phone number. All of this information is kept completely confidential, and will never be used for any other purpose.

Email: ______________________________ Phone: (______) ______–________
area code

Thank you for your time!

We welcome any additional comments you may have regarding transportation in your community. Please write them in the space below, and on the next page if needed.